Environmental Regulation and Household Well-Being: Evidence from China's War on Pollution[*]

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Abstract

This paper employs a quasi-experimental research design to shed light on how China's war on pollution affects household health outcomes. My results show that the stringent environmental regulation significantly reduced $PM_{2.5}$ concentrations, respiratory disease, pollution-related chronic disease, depression and medical expenditure for both young children and elderly. For infant birth outcomes, I document a significant reduction in preterm birth rate. Yet, there also exist heterogeneous effects across individuals whose job is of different pollution intensities. The mechanism analysis suggests that the shutdown of polluting firms, people's information search and avoidance behavior explain such health benefits. Back-of-the-envelope calculations suggest the health benefit of China's war on pollution is huge.

JEL classification: I12, I18,J13, J14, Q51, Q53, Q58

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1 Introduction

Over the past decades, tremendous efforts have been invested into the environmental regulation around the world. How these environmental policies affect the pollution level and household welfares, and how to evaluate the benefits and costs are at the core of both academic and policy field. Among those policies, the Clean Air Act implemented in the United Stats since 1970 and its amendments had been regarded as a successful policy with a deep influence on the U.S. economy and society. Extensive studies evaluate its comprehensive impacts, including the impact on pollution level (Greenstone, 2004; Auffhammer et al., 2009), health outcomes (Bishop et al., 2018; Hollingsworth and Rudik, 2021) and medical expenditure (Deschenes et al., 2017) and conclude with billons of monetized welfares improvements.

In developing countries, the "China's War on Pollution" since 2014 also received large attention (Greenstone et al., 2021, 2022; Dong et al., 2022; Heo et al., 2023). Although extensive literature documents its effectiveness, we have little direct evidence on how it induced health and other welfare improvements. In addition, the high pollution level and weak institution would also undermine the efficiency of regulation and make it difficult to evaluate the welfare outcomes.[1]

This paper exploits the question that whether or not the China's War on Pollution is effective in reducing the pollution concentrations, and if so, how this regulation-induced reduction affect the local household well-beings?

China's war on pollution is a wide framework under which a series of environmental policies were implemented. Previous studies mainly employed nationwide automatic air quality monitoring system (Greenstone et al., 2022; Dong et al., 2022) and key region policy (Karplus et al., 2018) to identify the causal impact of environmental regulation. Specifically, I employ a stringent environmental policy in China - "*Key Region Policy*" (henceforth, KRP) legislated through the *Amendment of Atmospheric Pollution Prevention and Control Law* on January 1, 2015 - for several reasons.[2] First, the legislation of KRP is the essential part under the whole framework of China's war on pollution, which provides a quasi-experiment reseach design in this paper. The KRP requires local government in key regions to comply with the reduction targets if its pollution concentration is above the standard numbers, which provides the geographic and time variation for identification (Karplus et al., 2018; Liu et al., 2021). Second, China's huge efforts were invested into pollution control since 2013, which offers an ideal setting for examining the impact of regulation on household welfare. According to Greenstone et al. (2021), China only took

[1] Greenstone and Jack (2015) summarizes four explainations in developing country that may account for the poor environmental quality and weak institutions: high marginal utility of consumption, high marginal costs of providing environmental quality, political economy and rent-seeking behavior, and market failures-induced biased marginal willingness to pay.

[2] https://www.mee.gov.cn/ywgz/fgbz/fl/201404/t20140425_271040.shtml

5 years to hit up the similar level of reduction in U.S., which took more than 20 years. Therefore, the evaluation of impacts on health welfare would be possible even at high pollution level. Third, the stylized facts show that fine particulate matter (i.e., $PM_{2.5}$) stays at its high level and drops sharply after 2014. The China's war on pollution deeply affect the whole society including health, labor market, export, firm dynamics and so on. Therefore, the evaluation of this newly implemented policy would complement new evidence to literature on previous regulation in China (e.g., Tanaka, 2015; Liu et al., 2021) and other developing countries (e.g., Greenstone and Hanna, 2014; Do et al., 2018).

To exploit the causal effects on welfare, I use a difference-in-differences (DID) research design that compares welfare outcomes in key region cities to non-key region cities. This city-level geographic variation induced by policy shock is commonly used in previous studies which employ the Non-Attainment status in US (Isen et al., 2017; Deschenes et al., 2017), CWS in Canada(Cherniwchan and Najjar, 2022) and key regions in China (Karplus et al., 2018; Liu et al., 2021).

For the policy effectiveness, my results provide robust evidence that the KRP significantly reduce $PM_{2.5}$ concentrations by 4.75 $\mu g/m^3$, about 7.9 percent point. I then measure the household well-beings using the health benefits of infants, children and elderly, because the infants and elderly both tend to be sensitive to air pollution. For infants health, the low birthweight rate and the preterm birth rate decrease by 0.2 and 0.79 percent point, respectively. For young children. the respiratory rate and outpatient rate drop by 6.1 and 4.8 percent point, respectively. The defensive investment evidence show that the medical expenditure drops by 15 percent point.[3] Meanwhile, I also document the evidence of health improvements among the elderly. My results show that the chronic and limitations in activities of daily living drops by 2.7 and 2.4 percent point, respectively. In addition, the respiratory rate and depression rate drops by 7.64 and 1.47 percent point, respectively.

To shed light on the heterogeneous effect, I separate the sample by their work type and further show that the elderly who take "Dirty jobs" have worse health outcomes, measured by insignificant respiratory reduction, higher probability of bad health and chronic disease rate. These comprehensive results show that those workers bears more regulation costs. Due to specific work environment (most of them work in manufacturing plant), those workers face higher level of pollution exposure so their health outcomes get worse and do not benefit from the environmental regulation.

Combining the above analysis, I employ the estimated coefficients to derive a simple back-of-the-envelope calculation with the health improvements benefits. I find that 4.75 units of predicted fine particulate matter reduction from the key region policy led to a 1 percent decline in preterm birth infants, which translates into 0.632 billion in year of

[3]The medical expenditure data in my sample is the annual total medical expenditure, while prior literature mostly employ the pollution-related expenditure.

2017. The reduced medical expenditure result 33.54 savings for a children per year.

This paper contributes to three strands of literature. First, this study informs the burgeoning literature on environmental regulation and its impacts on health, by focusing on a large developing country with high pollution and the most stringent regulation policy. The China's war on pollution and its large effort provide an interesting background and would complement the health benefits documented in prior literature on developed countries (e.g., Deschenes et al., 2017; Hollingsworth and Rudik, 2021; Marcus, 2021; Hansen-Lewis and Marcus, 2022). Although this paper resonates with prior work on China's environmental regulation, previous studies mainly employed an early policy from 1998-2006 (Tanaka, 2015; Liu et al., 2021). And the stylized facts indicate that the overall pollution level is still climbing and peaks around year of 2013 as shown in Figure 1. The KRP policy in this paper is also analyzed in previous studies, but they focused on firm behavior (Karplus et al., 2018; Greenstone et al., 2022; Dong et al., 2022) and city-level medical expenditure (Lu et al., 2021). Therefore, my study is the first to show that China's war on pollution had measurable impacts on population health. Due to the accessibility of a latest wave of China's largest survey dataset, i.e., the CFPS dataset, I offer consistent support for these findings using a novel source of data with a wide set of measurements including infant birth outcome and physical and mental health of children and elderly. Given the fact that pollution level in China is still high and far beyond the health standard suggested by World Health Organization (Greenstone et al., 2021), the true health benefits should be considered with caution in a more broad picture.

Second, my research also contributes to a large literature examining the environmental justice and the heterogeneous effects of pollution. Researchers have examined heterogeneous effect of environmental policy on household, including the racial differences, education differences (Marcus, 2021), socioeconomic differences and income differences (Hausman and Stolper, 2021; Hansen-Lewis and Marcus, 2022). These uneven results receive much policy attention with attempt to provide more assistance to those groups who bear more health risks during regulation. My heterogeneous results contribute to this literature by showing that individuals who take the pollution-intensive jobs would also face higher health risks measured by worse health status due to more pollution exposure and work intensity. In addition, unlike most previous research that has documented that low-educated individuals face more pollution risks and exhibit worse health benefits, this paper suggests that the regulation-induced better air quality also improve their health outcomes much.

Third, this paper also explores the role of information search and avoidance behaviors in reducing the negative effects of pollution. Using the detailed survey dataset and China's Baidu Index, I measure the avoidance behaviors with buying anti-haze masks and air purifiers, reducing outdoor physical exersice exposure and reducing work hours. The estimates indicate that the KRP policy significantly increases these avoidance behaviors and thus help protect health. This is consistent with findings in other studies that show information search and avoidance behavior determine the effect of pollution (Zhang and Mu, 2018; Ito and Zhang, 2020; Marcus, 2021; Greenstone et al., 2022; Hansen-Lewis and Marcus, 2022).

The remainder of the paper is structured as follows: Section I briefly reviews the relevant institutional background. Section II analyzes the history of KRP and variation source. Section III introduces the identification and specification. Section IV describes my data and characterizes my treatment and control groups with summary statistics and despriptive evidence. Section V presents and discusses estimated effects on a variety of health outcomes, and Section VI investigates the heterogeneous effects. Section VII exploits the mechanisms driving my main results. Finally, Section VIII provides a simple benefit analysis and then concluding remarks. An online Appendix contains detailed descriptions of data sources and includes additional analysis.

2 Policy background

The China government launched a series of environmental policies since 1990s. In 1998, the "Two Control Zone" policy was proposed aiming to regulate the SO_2 level of the cities on the two control zones (Tanaka, 2015; Liu et al., 2021). In 2006, China government regulates the firm emission by establishing the "Clean Production Law". And in the same year the central government initiated China's 11th Five-Year Plan which specify mandatory national emissions targets (Fan et al., 2019). And in 2010, the central government encompass the air quality into the promotion of local officers.[4]

Overall, the year of 2013 could be seen one of the watersheds in the development of environmental regulation (Greenstone et al., 2021; Karplus et al., 2021). On one hand, the pollution level hit the top during 2013. The media coverage and government warnings put more focus on the pollution concentration, which reflects the whole demand for better air quality in the society. On the other hand, under the whole framework of China's war on pollution, a series of stringent regulation policies is proposed and the Amendment of Atmospheric Pollution Prevention and Control Law was put into agenda and finally legislated in 2015.

2.1 History of The Key Region Policy

Key region policy in 1998.- This concept was first proposed in 1998 in an official document (known as the "two compliance policy") of the Ministry of Environmental Protection (MEP) with the intention to improve the air quality of some key cities (Liu et al., 2021).

[4]More China environmental regulation policy and related literature is summarized in the paper by Karplus et al. (2021); Greenstone et al. (2021)

The central government designated 47 prefecture-level cities as the first batch of cities as the key region cities with higher regulation stringency, most of which were municipalities, provincial capital cities, cities in special economic zones, major tourist cities, and coastal open cities. Although Liu et al. (2021) show that the 1998 version of KeyRegion policy significantly reduce the firm-level SO_2 emission since 2002, the environmental regulation authorities do not gain much political support, enforcement power and social focus in their policy period from 2002-2007. Therefore, the stylized facts indicate that the overall pollution level is still climbing and peaks around year of 2013, though the SO_2 emission drop sharply since 2002 as shown in Figure 1.

Proposition of Key region policy in 2012.- This renewed policy is called the "*Key-Region Air Pollution Prevention: the Twelfth-Five Years Planning*" and proposed by Ministry of Environmental Protection, National Development and Reform Commission and Ministry of Finance at December, 2012. The KRP is the first comprehensive air pollution prevention planning in China, which involves 19 provinces and 117 prefectures. The area under this policy is 1.32 million square kilometers. The area, population, economy and coal consumption would account for 14%, 48%, 71% and 52% in the whole nation, respectively.

Legislation.- After the proposition, the key region policy was legislated through the *Amendment of Atmospheric Pollution Prevention and Control Law* on Janurary 1, 2015 (counterpart of the Amendments of Clean Air Act in the U.S.). [5] According to the amendments, all governments at and above the county level should include air pollution prevention and control in their economic and social development planning and design concrete plans to reach the environmental quality standards by 2017.

2.2 Policy targets and variation source

According to the policy, the key region cities listed in the official document and alternative cities specified by the local province government need to comply with the National Ambient Air Quality Standard and finish the reduction targets. Cities that do not meet the standard would be recorded and local officers may thus be affected during the comprehensive evaluation and promotion.

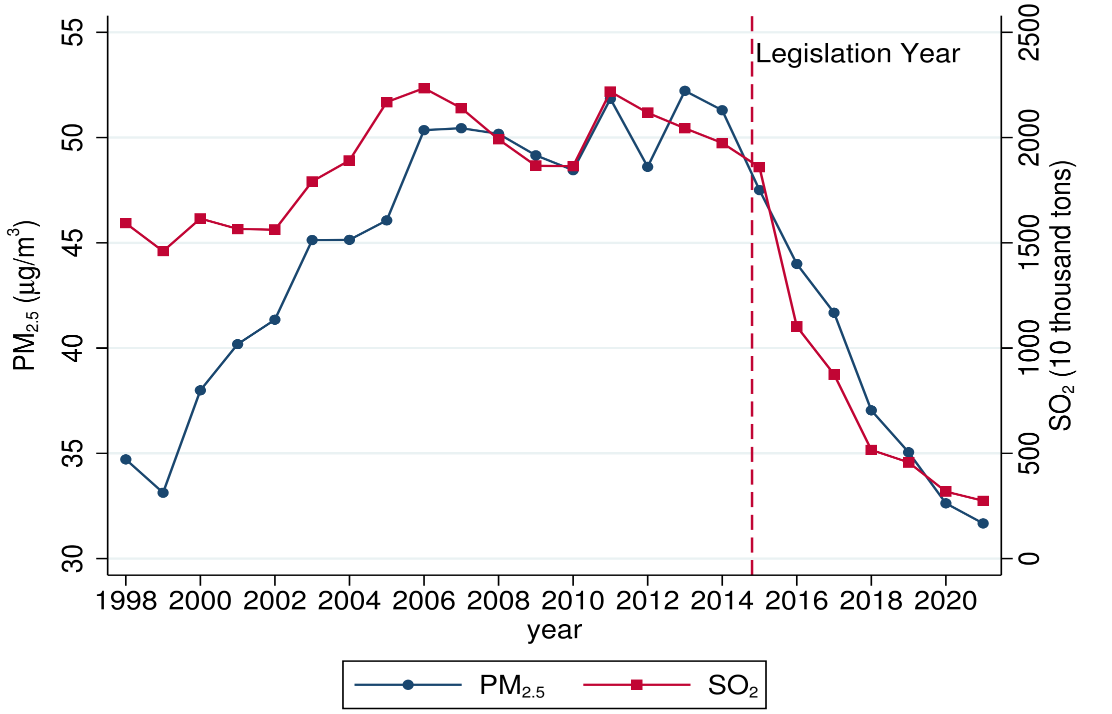
Most of key region cities are specified by the "*Key-Region Air Pollution Prevention: the Twelfth-Five Years Planning*".[6] The key region cities are composed of 67 prefecture-level cities in 19 provinces primarily located in the greater Beijing–Tianjin–Hebei area, the Pearl River Delta, the Yangtze River Delta and in some key cities across China (See the Figure 2).[7] In addition to the listed cities in this report, the central government also required the local province government to specify the municipal-level key region cities

[5] The procedure of the law could be seen by the link: https://climate-laws.org/geographies/china/laws/law-on-the-prevention-and-control-of-atmospheric-pollution

[6] see, http://www.gov.cn/gongbao/content/2013/content_2344559.htm

[7] Due to the limitation of my survey data, we only plot the cities with data.

Figure 1: $PM_{2.5}$ and SO_2 Trends in China

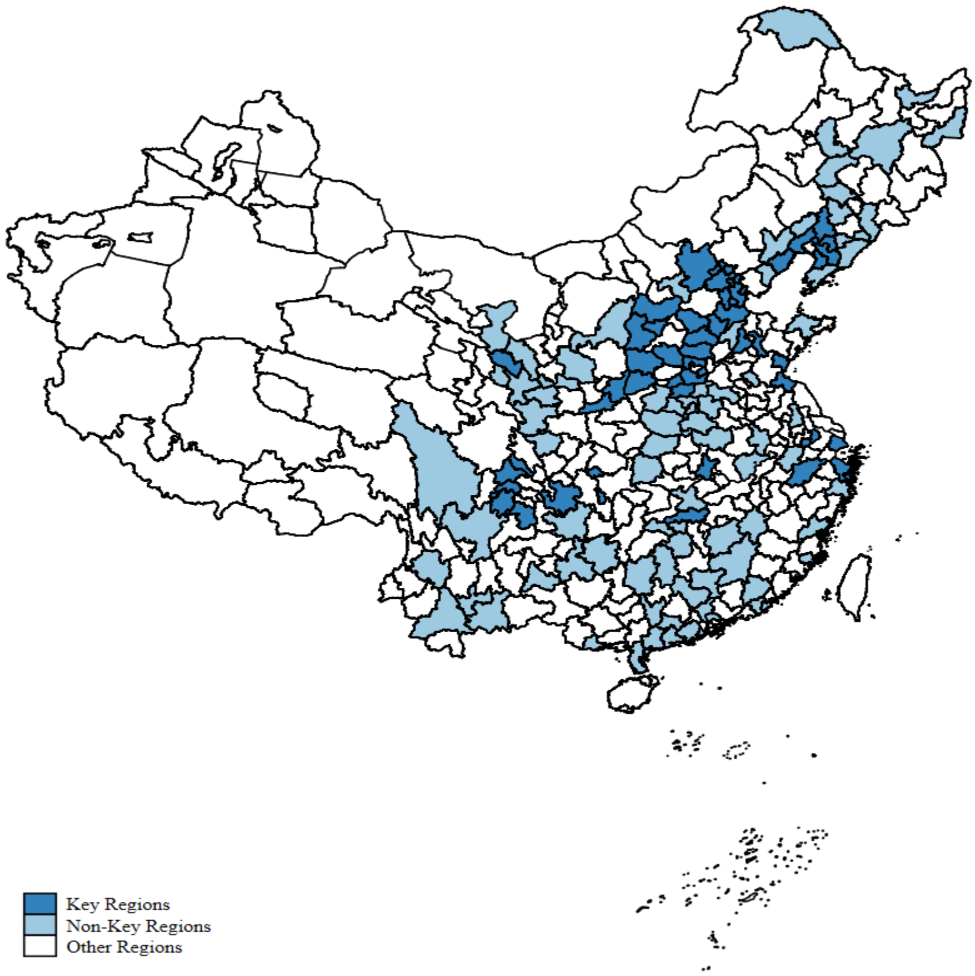


Notes: This figure plots the average annual pollution concentrations of $PM_{2.5}$ ($\mu g/m^3$) and SO_2 (10 thousand tons) over time from 1998 to 2021. Data of $PM_{2.5}$ is from the Atmospheric Composition Analysis Group in Washington University in St.Louis calculated by van Donkelaar et al. (2021), and SO_2 is from China Statistical Yearbook collected and published by National Bureau of Statistics of China (NBS).

according to their local economic and environment condition. I collect the key region city lists from each province-level government report.

Finally, the samples in this paper include 44 key region cities and 82 non-key region cities. In Figure 2, I depict the key region cities and non-key region cities in the map of China. The darker blue cities faced higher regulation pressure and are denoted as the treatment group in this paper. Therefore, I rely on this variation of regulation stringency for identification.[8]

Figure 2: The distribution of Key Region Cities in China



Notes: All 44 key region cities and 82 non-key region cities are included in my survey dataset. The blank area is not available in my datasets.

[8]In this paper, I focus on the $PM_{2.5}$ reduction effect, so I do not include the delta river area as the key region. Although they are denoted by the key region in this policy, their $PM_{2.5}$ level is much lower than the average. Liu et al. (2021) include this area as the key region area because of the SO_2 emission is high in this place due to larger number of manufacturing firms.

3 Research Design

This paper exploits whether the newly implemented KRP significantly increase the household welfare by using a DID research design. Under the DID framework, the DID estimator exploits two sources of variation in the regulation stringency specified by the KRP. First, I compare the years before and after the implementation of policy, i.e., the period treatment. Second, I leverage on the key region status and non key regions facing different level of regulation intensity, which provide the comparisons among cities. We also argue that this Key Region policy induced substantial variation that is plausibly unrelated to other determinants of well-being. Following prior literature which employs regulation policy as an quasi-experiment design (e.g., Curtis, 2018; Marcus, 2021; Hollingsworth and Rudik, 2021; Hansen-Lewis and Marcus, 2022), I exploit the variation of pollution levels in the "Key Regions" (counterpart to "Non-attainment" designated under US Clean Air Act). The key region cities are main pollution-intensive areas and are required by a legitimate policy to comply with the pollution targets in a specified time window. Therefore, I argue that the household in key region cities would face a higher level of environmental regulation stringency. The key region policy thus provide an ideal setting for quasi-experiment design (see, e.g., Karplus et al., 2018; Liu et al., 2021).

3.1 Identification

Identifying the causal effects of regulation relies on the fact that the exogenous policy only induce any changes in regional pollution concentrations, while keep others the same. Therefore, I face two primary empirical challenges: (i) measuring environmental stringency, and (ii) identifying the causal effects of regulation. First, there are several ways to measure the regulation stringency difference in literature. To avoid the measurement error, I directly choose the key region cities specified by the policy as the treatment group. This approach is also used in previous studies on key rgeion policy (e.g., Karplus et al., 2018; Liu et al., 2021). And for household welfare measures, I use the survey dataset which provides the direct answers of infant birth outcome, physician-diagnosed chronic disease and self-rating health status. These measures from the survey dataset are also commonly used in labor, health and environmental economics to measure the income, health, human capital and so on (e.g., Chen and Fang, 2021; Huang and Zhang, 2021; Deng and Lindeboom, 2022).

Second, the key identification assumption in this paper relies on the fact that the non-key regions provide valid counterfactual changes in individual well-beings indicators for the key region prefectures, had they not been treated, conditional on covariates. Two potential hypotheses may violate this assumption: (1) there is a systematic difference in preexisting trends in well-being measurements, and (2) the key region status is not orthogonal to factors explaining any changes in well-beings in the post-treatment period.

Therefore, I first initiate the pre-trend analysis based on Figure 6 that provide the initial evidence of city characteristics in both the treatment group and control group.

Also, I have to assume that there are no omitted time-varying, city-specific features correlated with the policy year and exposure that may affect the outcomes. This would be violated if, for example, another environmental policy is correlated with the regional pollution exposure. To avoid these concerns, I incorporate the province-year fixed effects.

3.2 Estimating the impacts of Key Region Policy

I first estimate the effect of Key region status on the regional pollution concentration and household well-beings. In an ideal research setting, the Key Region status is randomly assigned across cities, creating variation uncorrelated with baseline characteristics. In the absence of a randomized controlled trial, I use a simple difference-in-differences (DID) approach, the model is as follows:

$$y_{ict} = \alpha + \beta \text{KeyRegion}_c \times \text{Post}_t + X'_{ict}\gamma + \mu_c + \eta_t + \varepsilon_{ict} \quad (1)$$

where y_{ict} denotes the individual-level well-being measurement who resides in prefecture c and is surveyed in year t.[9] $KeyRegion_c$ is the treatment variables which equals 1 if the resident lives in the Key region. $Post_t$ is the time indicator equals 1 after the policy implementation. The coefficient of interest is β, which is the interaction of the key region exposure with the post-treatment variable. A set of control variables is denoted by X_{ict} including individual socioeconomic indicators such as age, age's square, gender, marriage status, education level, income and smoking status.[10] I control all of these variables because they are strongly related to health status and healthcare utilization. By doing this, this specification can avoid omitted variables and increase the accuracy of regression results.

The parameter β should capture any changes in individual well-being before and after the regulations, between the key regions treatment group and non-key regions since 2015. Ideally, if the air pollution regulation contributed to significant improvements in household welfare among key regions cities relative to non-key regions cities, I should observe a significant β.

City-specific time invariant characteristics are denoted by μ_c. τ_t is the year fixed effects and can be used to control for the shocks common to all cities in a given year. And ε_{ict} is an unobservable error term. Standard errors are clustered at the city level. Because most of the surveys take place in June or July (i.e., summer vacation), I ignore the month

[9]For the examination of policy effectiveness, I employ the $Pollution_{c,t}$ to denote the pollution level in city c in year t, which is calculated from the satellite-based Aerosol Optical Depth (AOD) retrievals.

[10]To examine the impact on pollution concentration, this vector contains GDP per capita, population, share of secondary industry over the gdp, share of labor in manufacturing industry and fiscal expenditure.

script.[11]

For all regression, I use a weighted regression to reduce the dominance of individual living in large cities in the estimation results. Specifically, all regressions are weighted by the inverse of the square root of the number of population for each cities to control for the potential concern of uneven distribution of survey participants across different cities. Although the two national survey datasets employed in this paper use multiple statistical tool to select the surveyed cities and in China, previous studies also use this weighted regression to improve statistical power (see, Huang and Zhang, 2021). Detailed sampling method is provided on the website of both datasets.

To exploit the impact on infant birth outcome, I use the cohort DID regression, which takes the following form:

$$y_{ict} = \alpha + \beta \text{KeyRegion}_c \times \text{Post}_{it} + X'_{ict}\gamma + \mu_c + \delta_t + \varepsilon_{ict} \tag{2}$$

where where outcome y_{ict} is the low birthweight and preterm birth rate for infant i, born in city c, in year t. And $Post_{it}$ is a dummie variable that equals 1 if the infant i was born after the legislation of key region policy since year of 2015. The difference to the baseline regression is the δ_t, which is now the birth cohort fixed effects ranging from year of 2011 to 2020.[12] The birth cohort fixed effects are important because they represent the cohort year time-varying fixed effects. In some specifications, I also report the estimation results controlling family-level fixed effects.

3.3 Event Study

I also examine the identification assumption using an event-study type analysis:

$$y_{ict} = \alpha + \sum_{t=2009}^{2020} \beta_t \text{KeyRegion}_c \times \text{Year}_t + X'_{ict}\gamma + \mu_c + \eta_t + \varepsilon_{ict} \tag{3}$$

where β_t captures the extra time effect on well-beings. The hypothesis is that there is no significantly different trend between the key regions and non-key regions before the introduction of the regulation policy. In Figure 5, I show that β_t before introduction of the policy, treated and control groups are not significantly different; i.e., they have a similar trend. One potential threat to this specification could arise if local KRP implementation is correlated with changes in alternative socioeconomic conditions. For further identification check, I also show that several socioeconomic variabes present the similar trends during policy period in Figure 6 with their *p*-values.

[11] Following Huang and Zhang (2021), I do not incorporate the individual fixed effect in the regression, because individual fixed effects may exaggerate the attenuation bias caused by measurement errors.

[12] In the baseline regression, the year fixed effect includes the year of 2010, 2012, 2014, 2016, 2018 and 2020 due to the biennial survey dataset.

4 Data and Descriptive Evidence

In this paper, I combine data from several main sources from 2010 to 2020: including the Aerosol Optical Depth (AOD) pollution dataset, China Family Panel Studies (CFPS), and China Health and Retirement Longitudinal Study (CHARLS) survey dataset. The CFPS dataset provides the household variables of children birth outcome and elderly health measures, while the CHARLS focuses on the health status of old people. Overall, the two survey datasets are commonly used in literature on labor, development, health and environmental economics in China.

China Family Panel Studies (CFPS).- The CFPS dataset is a nationally representative sample of Chinese communities, families, and individuals that covers 25 of China's 31 provinces/regions and 162 cities. The waves of survey I use are 2010, 2012, 2014, 2016, 2018 and 2020. Since most surveyed households do not respond during each wave, this is an unbalanced panel dataset. Finally, I have the 100,605 observations that aged 45 and above and 50,294 observations of children from this dataset.

China Health and Retirement Longitudinal Studies (CHARLS).- The CHARLS is also a commonly used dataset which aims to collect the information of old people ages over 45 and older. This survey is the Chinese equivalent of Health and Retirement Survey (HRS) in US. The CHARLS dataset started in 2011, and this study uses the 2011, 2013, 2015 and 2018 waves of the CHARLS. Finally, I have the 77,100 observations that aged 45 and above from CHARLS dataset. The CFPS and CHARLS dataset could be merged to form a large sample representing China residents from all ages, which also provide more household characteristics in China. Huang and Zhang (2021) merged the CFPS and CHARLS dataset to analyze the impacts of pension on health, labor supply, income and expenditure, and confirmed its feasibility.

Pollution Data: My pollution measure is the monthly concentration of fine particulate matter ($PM_{2.5}$) derived from satellite-based Aerosol Optical Depth (AOD) retrieval techniques maintained by the National Aeronautics and Space Administration (NASA), and is widely employed among previous studies (see, Fu et al., 2021; Khanna et al., 2021).[13] I access these satellite-based $PM_{2.5}$ estimates from the dataset provided by van Donkelaar et al. (2021). I use the AOD data because it provides the most comprehensive measure of air pollution across China's geography and over time, and this data is more reliable without data manipulation. The AOD measures the extinction of the solar beam by dust and haze and can be used to predict pollution even in areas lacking ground-based monitoring stations (van Donkelaar et al., 2021).

To match the individual's welfare to its pollution exposure, I argue that over 90 percent of the total interviews in both survey dataset are conducted between July and Septem-

[13]The NASA satellite data could be accessed from the NASA website, see MERRA-2 data: `https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_5.12.4/summary`; The AOD measure in this paper is from `https://sites.wustl.edu/acag/datasets/surface-pm2-5/`;

ber. [14] Therefore, I define the time window of exposure to pollution within 12 month before the survey time. For example, for an individual surveyed at August 2020, I use the average concentration of $PM_{2.5}$ from September 2019 to August 2000 for that individual.

Infant and children health: The infant birth outcome from the CFPS dataset has been shown to be sensitive to air pollution and is essential for later life outcomes in labor and health economics (Isen et al., 2017; Currie and Walker, 2019). Infant health is also ideal for the measurement and avoidance of endogeneity. I choose the low birthweight and prematurity as two measures of infant birth outcome. Besides, I employ the physician-diagnosed respiratory chronic diseases to objectively measure children health.[15] The CFPS dataset provides a wide set of household information including year and month of birth, place of birth, and whether individuals were born in a rural area. I separate those samples by rural areas and urban ares. The reason for this intervention is because that the KRP mainly focuses on the urban pollution control and urban pollution is more severe, thus the urban sample should be more sensitive to the pollution reduction and reflect the reliable estimates.

Elderly health: I employ individuals from CHARLS dataset and CFPS dataset aged 45 and older to denote the health change for the elderly. The previous studies show that the elderly is also sensitive to the pollution exposure (Zhang et al., 2017; Ao et al., 2021) and environmental regulation(Lai, 2017; Hollingsworth and Rudik, 2021; Hansen-Lewis and Marcus, 2022). The measurement of household health mainly include the physical health, mental health and health expenditure. Following Lai (2017), Chen and Fang (2021) and Huang and Zhang (2021), I also use the measures with four main dimensions: Activities of Daily Living (ADL), Cognitive ability, Self-reported overall health condition and Medical expenditure.[16] In addition to these comprehensive health measures, because this paper focuses on the pollution reduction caused by key region policy, I also choose the chronic status, respiratory disease, asthma and outpatient as the most important variables to represent the household health status impacted by pollution changes.[17]

Other controls: CFPS and CHARLS dataset provide several control variables, includ-

[14] Previous studies also use this method to match the pollution exposure with the health effects (see, Zhang et al. (2017); Deschenes et al. (2020)).

[15] The CFPS documents the question that "During the past six months, have you had any doctor-diagnosed chronic disease?" And if the answer is yes, it continues: "What was your doctor's diagnosis of the disease you suffered from?" The CFPS records the detailed disease codes, and the pollution-related chronic codes is summarized in the Appendix.

[16] These measures are also employed in existing medical and toxicology literature, though the mortality is a more convincing measure for calculating the lower bound of welfares. The CHARLS and CFPS dataset do not provide mprtality information, so here I mainly focus on the comprehensive health measures.

[17] The CHARLS survey provides detailed information about the incidence of 14 different types of illness in the last 4 weeks, including hypertension, dyslipidemia, diabetes, cancer, chronic lung diseases, liver disease, heart attack, stroke, kidney disease, stomach disease, emotional problems, memory-related, arthritis and asthma. The CFPS survey provides detailed chronic disease codes diagnosed by physicians during last 6 months, including respiratory and other chronic disease.

ing gender, age, education years, and marital status, rural/urban type, household income and smoking status. The socioeconomic information can help me capture family heterogeneity across different cities. For impacts on elderly, I include the above variables; For children regression, I also control for infant gender and family fixed effect. By incorporating these socioeconomic variables into regression, I could control for individual characteristics that may affect their health status. Following Hansen-Lewis and Marcus (2022) and Alexander and Schwandt (2022), I also include an additional controls in the infant birth outcome regression.

Table 1 and 2 contain descriptive statistics on the variables used in my analysis. The average municipal-level pollution concentration is about 59.88 $\mu g/m^3$ in the treatment group and approximately 43.97 $\mu g/m^3$ in the control group. The summary statistics for socio-demographic variables by treatment show that the key region cities have higher chornic rate and respiratory rate, also the children health is worse in those ares.

Before the estimation results, I first plot the raw data. Figure 3 plots the trends of the pollution level between key region cities and non-key region cities from 2009 to 2020. This figure suggests that the whole $PM_{2.5}$ pollution concentration decreased since 2014. To further compare the magnitude of reduction between the two group, panel (a) of Figure 4 shows that while the pollution level between key region area and non-key region area is high in pre-policy period and has the same downward trend, the pollution level in key region cities drops sharply since 2014-2015. Panel (b) of Figure 4 sets both trends starting at zero, and the negative values on the y-axis indicate pollution reductions. The result also indicates that the higher level of regulation stringency in key region cities reduce the pollution much. Overall, these figures show that after the year of legislation of KeyRegion policy, pollution reduction in key region drops more sharly. Therefore, I employ this pollution reduction induced by different regulation stringency as the variation for identification.

Table 1: Summary Statistics

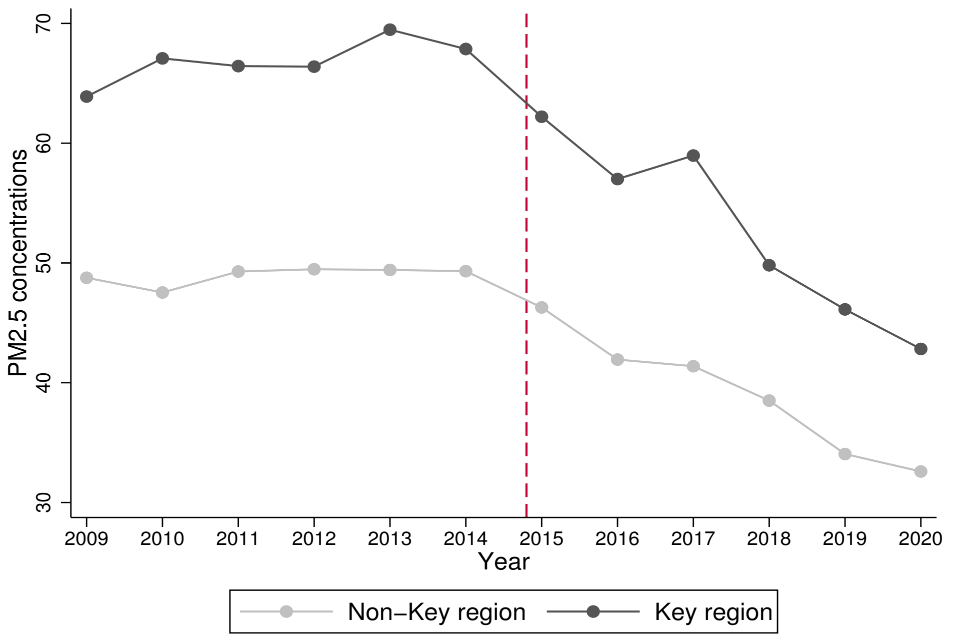
	Key Region		Non-Key Region	
	Mean	SD	Mean	SD
City-level characteristics				
$PM_{2.5}$ ($\mu g/m^3$)	59.88	18.6	43.97	15.34
Panel A. Elderly health (CFPS dataset)				
Individual characteristics				
Chronic	0.228	0.420	0.223	0.416
Respiratory	0.096	0.294	0.088	0.283
Feel uncomfortable	0.328	0.469	0.382	0.486
Bad health	0.190	0.392	0.232	0.422
CES-D score	3.313	3.265	4.024	3.484
Depression	0.054	0.227	0.080	0.272
Log of Medical Expenditure	7.328	1.760	7.127	1.719
Controls				
Age	60.28	10.58	59.48	10.49
Male	0.473	0.499	0.478	0.499
Marriage	0.823	0.380	0.802	0.398
Education Years	6.393	4.69	4.942	4.72
Log of Individual Income	8.437	1.916	7.787	2.096
Rural *hukou*	0.576	0.494	0.731	0.443
Panel B. Elderly health (CHARLS dataset)				
Individual characteristics				
Chronic	0.255	0.435	0.246	0.431
Asthma	0.025	0.158	0.029	0.169
Lung	0.063	0.243	0.083	0.276
ADL	0.082	0.275	0.097	0.296
IADL	0.120	0.325	0.172	0.377
Controls				
Age	60.80	10.17	60.53	10.12
Male	0.483	0.499	0.481	0.499
Marriage	0.821	0.382	0.793	0.405
Education Years	9.55	6.34	8.79	6.72
Smoking status	0.223	0.416	0.223	0.416
Rural *hukou*	0.672	0.469	0.704	0.456

Notes: This table shows summary statistics for the pollution concentration and household welfare outcomes between 2009 and 2020. The sample is separated by the key region status. The calculation of these health outcomes are defined in the main text. The health outcomes and individual-level characteristics are abstracted from the CFPS and CHARLS database. The city-level characteristics are from China Statistical Yearbook. The pollution concentration is accessed from the database calculated by van Donkelaar et al. (2021) and then matched with China cities.

Table 2: Summary Statistics - Children Health

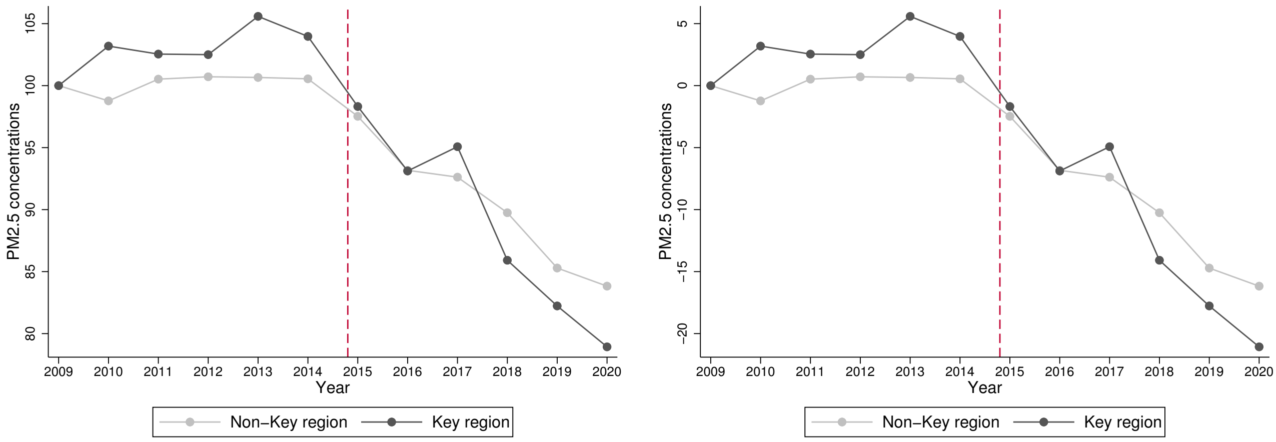
	Key Region		Non-Key Region	
	Mean	SD	Mean	SD
Panel C. Infant Birth Outcome				
Birth weight (gram)	3278.628	497.00	3209.168	555.06
Gestation period (month)	9.54	0.67	9.42	0.63
Low Birth Weight	0.043	0.203	0.062	0.241
Prematurity	0.056	0.231	0.047	0.213
Panel D. Children Health Outcome				
Respiratory	0.688	0.462	0.658	0.474
Outpatient	0.494	0.50	0.412	0.49
Inpatient	0.093	0.291	0.118	0.323
Illness	0.275	0.446	0.284	0.451
Log of Medical Expenditure	6.245	1.38	5.905	1.44
Controls				
Male	0.505	0.499	0.533	0.498
Rural	0.338	0.473	0.649	0.477

Figure 3: Key Region and Non-Key Region $PM_{2.5}$ Level



Notes: This figure plots the trends of ambient $PM_{2.5}$ concentrations between key rgeion cities and non-key region cities across time.

Figure 4: $PM_{2.5}$ Trend Between Key Region and Non-Key Region



(a) $PM_{2.5}$: 100 as the benchmark (b) $PM_{2.5}$: 0 as the benchmark

Notes: The panels plot ambient $PM_{2.5}$ concentrations across time and space by setting the benchmark as 100 $\mu g/m^3$ and 0 $\mu g/m^3$, respectively. Panel A plots average ambient $PM_{2.5}$ concentrations when the starting unit is at 100 $\mu g/m^3$. Panel B sets the starting unit at 0 $\mu g/m^3$, and thus the negative values on the y-axis indicate the reduction of $PM_{2.5}$ concentrations since year of 2009

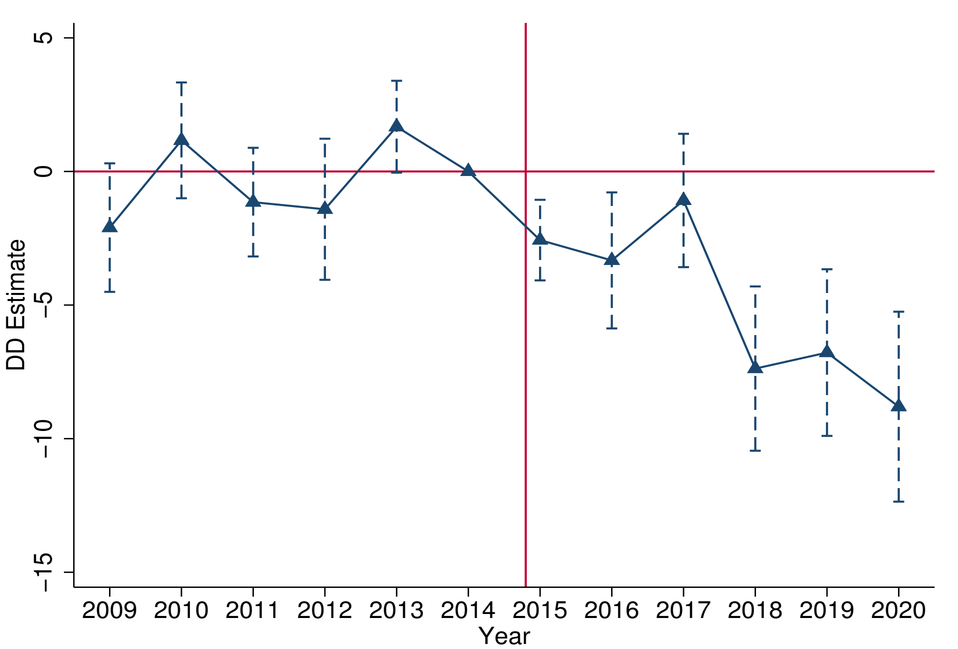
5 Results

5.1 Effectiveness of Key Region Policy

Pretrends analysis (1): Event study.- I first test the policy's effect on the regional $PM_{2.5}$ concentrations. To ensure satisfaction with the strong identification hypothesis that the treatment group would have tracked the same trend as the control group in the absence of the KeyRegion policy, I begin by checking on the identification assumption. Figure 5 presents coefficients and 95 percent confidence intervals on the KeyRegion-Year interactions from the regressions of $PM_{2.5}$ from 2009 to 2020. As Figure 5 shows, before the policy was enacted, the coefficients of KeyRegion-year interactions do not significantly differ from 0, indicating that key region and non-key region have similar pollution emission trends. After the policy was enacted, the coefficients of KeyRegion-Year interactions are less than 0, indicating a significant reduction in $PM_{2.5}$ concentrations in the treatment group compared to the control group. In the first year after the legislation of key region policy, I estimate that the pollution concentration decreases by 3.8 units, a 6.35 percent drop in mean concentrations.

Pretrends analysis (2): Descriptive evidence.- Second, I provide the initial evidence and plot the economic indexes over the calendar years for both treatment group and control group. Figure 6 presents the pattern for the logarithm of GDP per capita, population, fiscal expenditure, number of beds in hospital, number of physician and wage. The time trends between the key region are and non-key region are fairly parallel. These trends

Figure 5: Event study of Key region policy on pollution



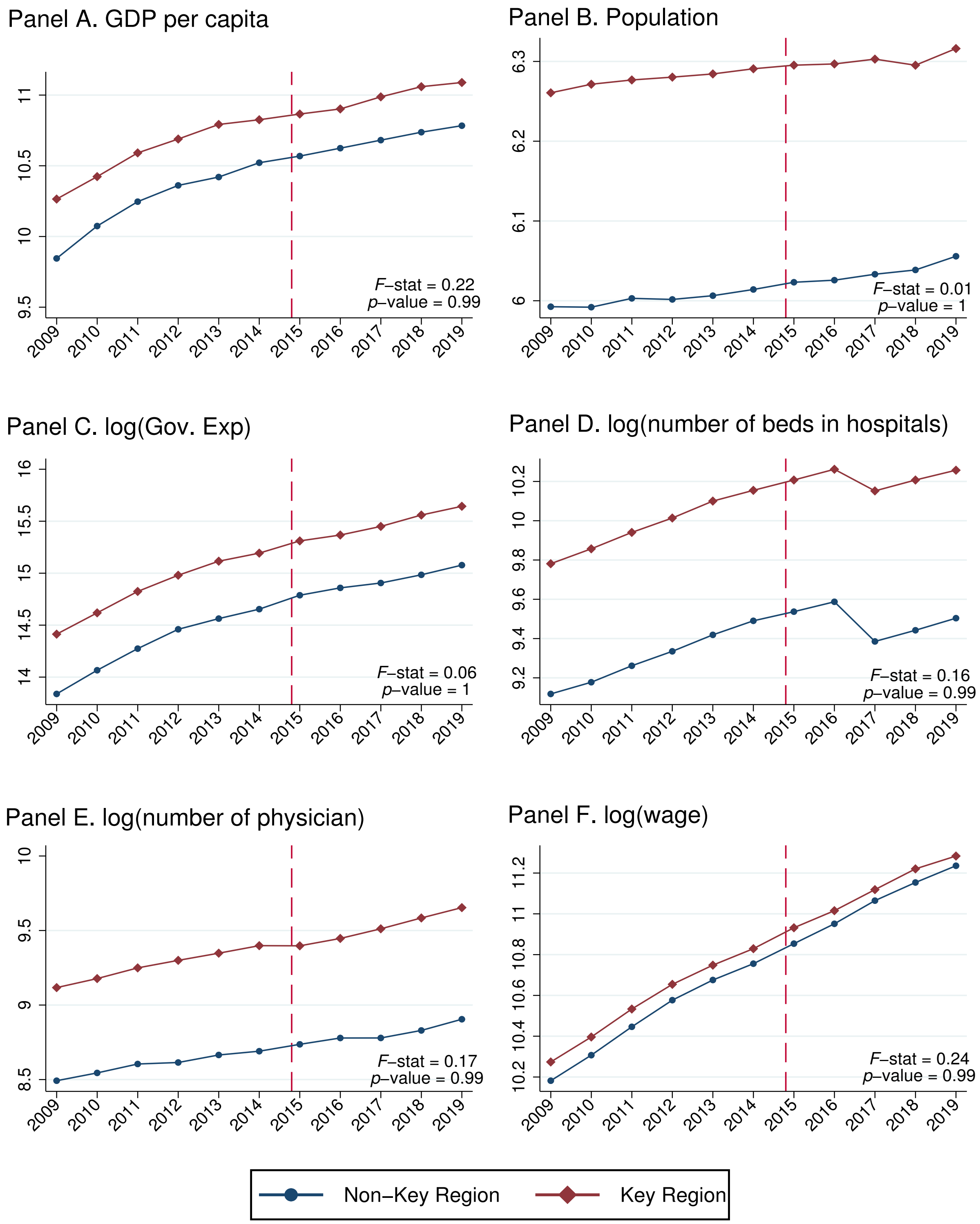
Notes: This figure plots the estimated coefficients of KeyRegion × Year dummy variables. The regression controls for year fixed effects, city fixed effects and annual city-specific economic controls. The dependent variable is ambient $PM_{2.5}$ concentrations. Brackets denote 95 percent confidence intervals, calculated from robust standard errors clustered at the city level. The reference year is 2014.

suggest that there are no significant differences in the city-level economic indexes. In each figure, I also conduct *F*-tests for parallel trends and report their *p*-values. Overall, the tests and the direct figure evidence suggest there are no significant nonparallel trends.

DID results.- The DID results on the environmental performance corresponding to Equation (1) are shown in Table 3. The baseline result in column (1) controls for only city fixed effects and year fixed effects. The estimate for KeyRegion × Post is significantly negative, implying that the harsher key region policy reduce the pollution levels by 4.75 $\mu g/m^3$ (about 7.9 percent).[18] Given the fact that most of China's policies were designed at the provincial-level, I also control for province-by-year fixed effects to capture the policy factors at the province level. These results also offer evidence that the new air pollution control policy is effective at reducing city-level $PM_{2.5}$ concentrations in key region cities. Column (2) includes province-by-year fixed effects and this reduces the impact of key region policy to 2.2, suggesting that key region policy led to a 2.2 $\mu g/m^3$ fall in $PM_{2.5}$. Relative to the average level of fine particulate matter, this represents a 3.67 percent decline. As I add city-specific socioeconomic characteristics in column (3) and (4), neither coefficient meaningfully changes. The inclusion of city-specific socioeconomic characteristics is important for my identification since it help guard against the possibilities that my specification ignore any important city changes other than regulation stringency.

[18]The mean number of $PM_{2.5}$ in key region is 59.88, so the percent change is 7.9 percent.

Figure 6: Examination of Pretrends in Key Region Cities and Non-Key Region Cities



Notes: The economic indexes from different cities are from the China City Statistical Yearbooks. Each figure plots the mean values of the logarithm of the economic indexes from 2009 to 2019. The vertical line indicates the legislation of the Key Rgeion Policy. The p-values are shown to test the equality of coefficient estimates for cities located in key region and non key region areas.

Table 3: Difference-in-Differences Estimates of Pollution Concentrations

Variables	$PM_{2.5}$			
	(1)	(2)	(3)	(4)
KeyRegion × Post	-4.752[a]	-2.235[a]	-3.761[a]	-2.116[a]
	(0.988)	(0.618)	(0.897)	(0.609)
City Characteristics			X	X
City FE	X	X	X	X
Year FE	X		X	
Province-Year FE		X		X
Obs.	2425	2026	2064	2020
R^2	0.936	0.979	0.939	0.979

Notes: Standard errors are clustered at the city level. KeyRegion equals 1 if a city is denoted as the Key region cities for controlling pollution; otherwise, KeyRegion equals 0. Post equals 1 for all years after 2015 (legislation period); otherwise, Post equals 0. The control variable vector contains GDP per capita, population, share of secondary industry over the gdp, share of labor in manufacturing industry and fiscal expenditure. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

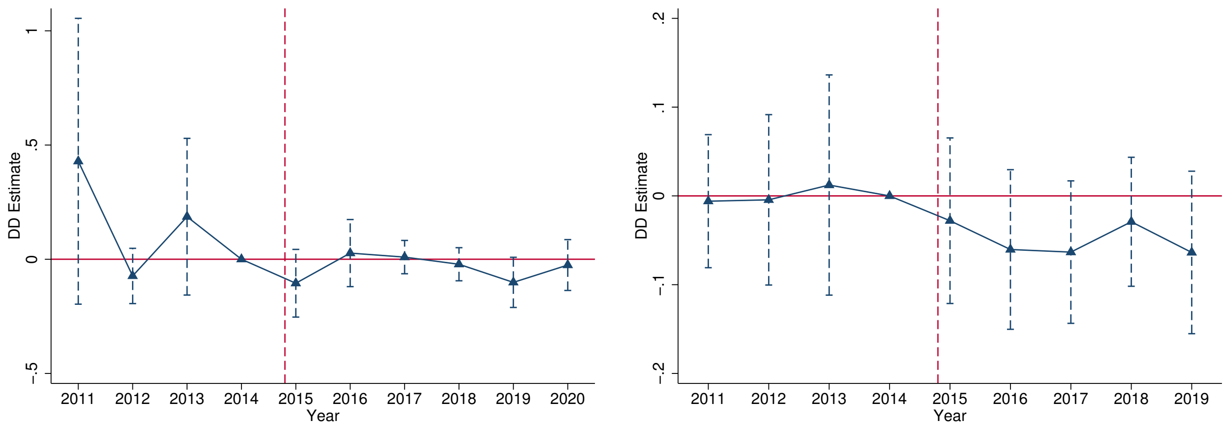
5.2 Impacts on Household Well-Beings

5.2.1 Children Health

Infant Health.- Figure 7 shows the event study of the key region on probability of low birthweight and preterm birth during the sample period. The decrease in rate between 2014 and 2015 is related to increased compliance with pollution reduction targets. Both figures show a steady decline since the legislation year. The reduction of preterm birth rate is more significant, while the low birthweight rate decrese since 2018. Although there is no immediate and dramatic decline in the probability at the legislation year, and in some years the coefficients are still insignificant after the policy. I argue that because the pollution concentration is still at high level, the gestation period usually takes 8 to 11 months. Also, the pregnant mother has been impacted by the high pollution concentrations for a long time. As the key region policy was legislated and pollution intensity began to decline, the overall health benefits would arise steadily after the policy year. More evidence would be complemented to this paper in the future study with new data.

Columns (1) to (4) in Table 4 show that the KeyRegion policy significantly reduces the probability of low birthweight rate and prematurity rate for urban infants with and without family fixed effects. Column (1) and (3) are the baseline estimates with year and city fixed effects, and results indicate that key region policy reduced the effect of $PM_{2.5}$

Figure 7: Event Study of KeyRegion on Infant Birth Outcomes



(a) Low Birthweight

(b) Preterm Birth

Notes: The panels plot event study estimates of key region policy on infant birth outcome across rural/urban type. Panels A and B present the impact on low birthweight and preterm birth rate, respectively. The regression includes birth cohort year fixed effects, city fixed effects, and controls for the age, age's square and gender type. The regression is weighted by the square root of the number of population in that city. Coefficients are denoted by the dots and the vertical line and whiskers denote the 95 percent confidence interval of the estimates. These solid trend lines reveal a distinct downward trend starting in 2015 for preterm birth rate. In panel B, the birth sample in 2020 is ignored because the sample size is less and with outliers.

exposure on low birthweight by 1.6 percent and preterm birth by 2.6 percent. Although the results on low birthweight are insignificant, we can not infer that there is no impacts on this variable. The insignificant results of low birthweight may due to the data limitation, which shows that the low birthweight rate in key region cities is less as shown in Table 2. This is also the limitation of survey dataset in my paper, so the unrelated results should be considered with caution. The future study which employs larger administrative dataset would complement to my findings. These results suggest that effects of key region policy on infant health are largely concentrated on the urban areas and in terms of preterm birth.

For the comparison of magnitude, here I employ the health benefits of infant birth outcome estimated by Marcus (2021), Alexander and Schwandt (2022) and Hansen-Lewis and Marcus (2022). Marcus (2021) show that facility upgrades reduced the effect of leak exposure on low birthweight by 1 percentage point and preterm birth by 0.3 percentage. Hansen-Lewis and Marcus (2022) show that ECA led to a 2 percent decline in low birth weight infants. This paper finds a 2 percent decline in preterm birth rate, indicating that the reduction of high pollution in China brought similar health benefits to the household.

Children Health.- The reduced pollution is associated with less respiratory disease and hospital visits among young children. Columns (1) through (8) of Table 5 document the effect of key region policy on a set of health outcomes for every urabn young children in

Table 4: The Effect of Regulation on Infant Birth Outcomes

	Low Birthweight (Yes=1)			Preterm Birth (Yes=1)		
	(1)	(2)	(3)	(4)	(5)	(6)
KeyRegion × Post	-0.0020	-0.0046	-0.0157	-0.0105[a]	-0.0069	-0.0088
	(0.006)	(0.009)	(0.012)	(0.003)	(0.005)	(0.010)
Obs.	1569	1534	465	2388	2366	1337
R^2	0.118	0.211	0.695	0.070	0.158	0.740
Family FE			X			X
City FE	X	X	X	X	X	X
Cohort FE	X		X	X		X
Province-Cohort FE		X			X	

Notes: The sample is from the CFPS (2010-2020) for infants. The covariatesin the regressionsin each column include dummies for gender, survey year and city. I also control for the family fixed effect in column (2) and (5). All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by [a], [b], and [c], respectively.

panel A. The overall impact on respiratory, outpatient and log of medical expenditure is statistically, indicating that the key region policy reduced 6 percent of respiratory and 4.8 percent of outpatient for urban children. However, the results on inpatient and illness are not statistically significant, indicating that the reduced pollution has less impacts on hospitalization rate and illness. This insignificant effect reflects how pollution affect human beings and can provide an additional robustness check for the estimations (i.e., the reduced pollution do not significantly affect the health status other than respiratory).

A better health outcomes would also indicate a lower healthcare expenditure, and further increase the welfare through higher consumption and saving. To capture this financial welfare caused by pollution reduction, I examine the out-of-pocket medical expenditure.[19] I regress the log of annual out-of-pocket medical expenditure on my DID variables and results in column (9) of Table 5 show that the KeyRegion policy decreases out-of-pocket medical expenditure by 13.6 percent and 17.6 percent for urban children sample and rural children sample, respectively.

Panels B of Table 5 presents the same regression results when using the rural children sample. The urban area has more construction sites, industrial firms, cars and less trees and plants, while the rural area usually has less population density and better air quality. It is no surprising to find that the respiratory effect is not statistically significant, while the

[19]This medical expenditure includes all medical expenditure, and do not separate the air pollution related expenditure with others. I employ this total medical expenditure value as a proxy for the air pollution induced expenditure, and this measure in CFPS is also employed in previous pollution studies (e.g., Yao et al., 2022).

effects on outpatient and medical expenditure remain significant. This indicates that the reduced pollution concentration in urban area has a more pronounced effect on children health outcomes.

The overall results show that there is a large and statistically significant effects of the key region policy on children health. This relationship is demonstrated in Figure 8, which shows downward trends of respiratory rate and log of medical expenditure, with city fixed effects and time fixed effects. While the coefficients are not clearly different with zero since year of 2015, there is an obvious downward trend for urban children sample (Panel A and C of Figure 8).

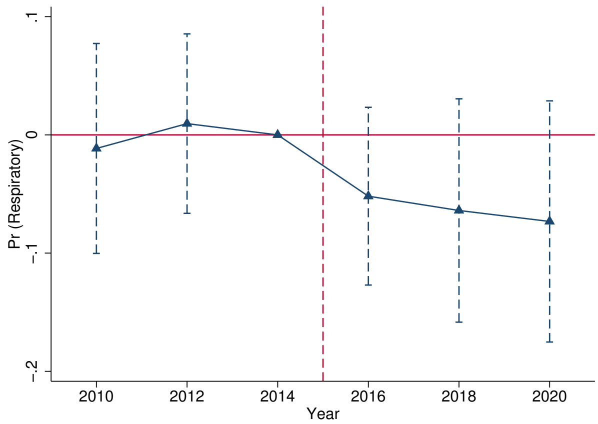
Figure 9, 10 and 11 present the insignificant impacts of KRP on outpatient, inpatient and illness, respectively.

Table 5: The Effect of Regulation on Children Health Outcomes

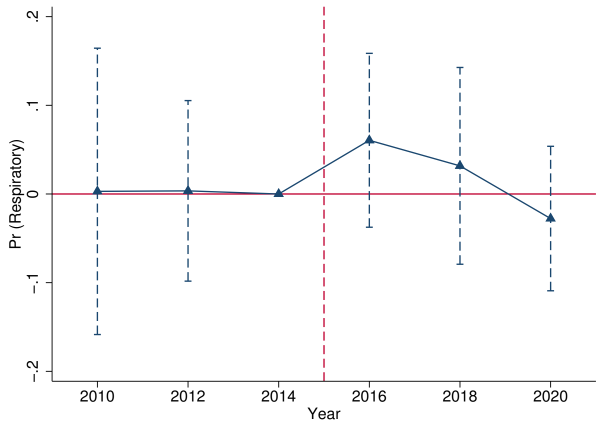
	Respiratory (Yes=1)		Inpatient (Yes=1)		Outpatient (Yes=1)		Illness (Yes=1)		Medical Expenditure (Log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Urban children sample										
KeyRegion × Post	-0.061	-0.051	0.016	0.038	-0.037	-0.048^c	-0.005	0.019	-0.150^b	-0.094
	(0.043)	(0.066)	(0.016)	(0.029)	(0.023)	(0.024)	(0.012)	(0.016)	(0.058)	(0.077)
Obs.	12301	10795	14130	12518	16020	14357	18716	17114	13001	11323
R^2	0.105	0.382	0.074	0.356	0.118	0.405	0.085	0.347	0.148	0.508
Panel B. Rural children sample										
KeyRegion × Post	0.019	0.024	-0.006	0.003	-0.055^b	-0.091^a	-0.032^c	-0.026	-0.169^b	-0.218^b
	(0.025)	(0.038)	(0.022)	(0.030)	(0.023)	(0.030)	(0.018)	(0.023)	(0.082)	(0.104)
Obs.	17162	15896	18952	17581	23549	22275	27430	26231	18232	16875
R^2	0.129	0.375	0.077	0.328	0.131	0.380	0.081	0.310	0.140	0.479
Family FE		X		X		X		X		X
City FE	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for children from birth to age 15 years. The covariatesin the regressionsin each column include dummies for gender, age, age's square, survey year and city. I also control for the family fixed effect in column (2), (4), (6), (8), (10). All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

Figure 8: The Effect of Regulation on Children Health Outcomes

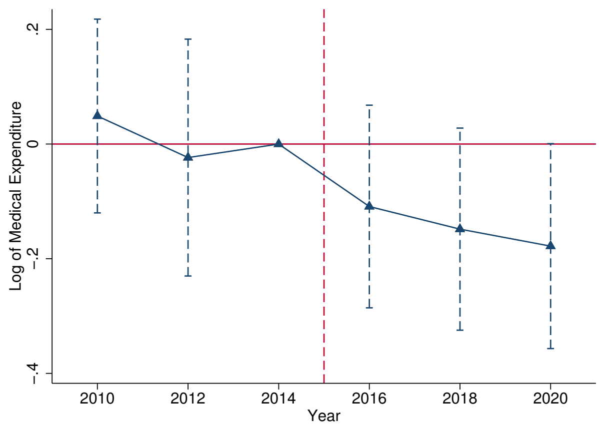


(a) Urban Children: Respiratory



(b) Rural Children: Respiratory

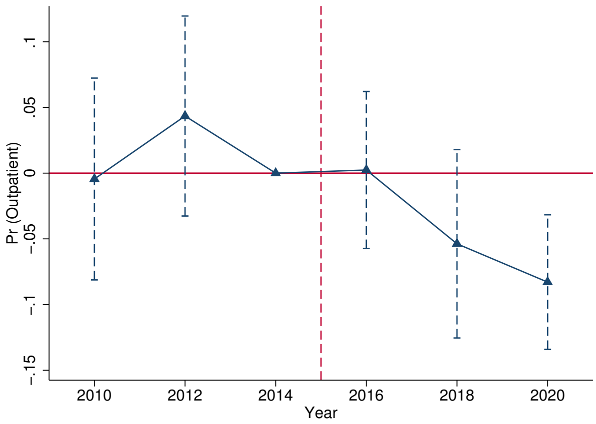
(c) Urban Children: Medical Exp



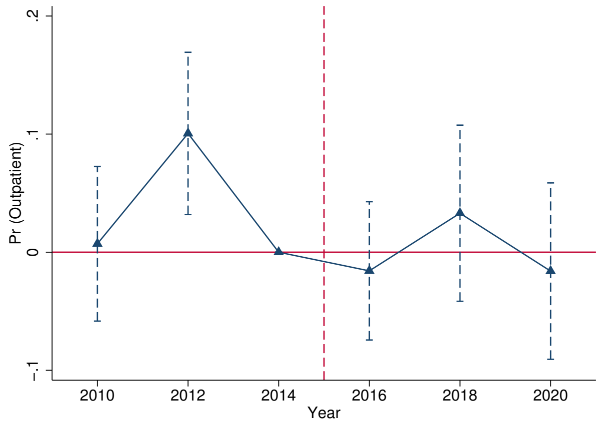
(d) Rural Children: Medical Exp

Notes: The panels plot event study estimates of key region policy on infant birth outcome across rural/urban type. Panels A and B present the impact on chornic respiratory disease rate across urban/rural type. Panels C and D present the impact on log of medical expenditure across urban/rural type. The regression includes birth cohort year fixed effects, city fixed effects, and controls for the age, age's square and gender type. The regression is weighted by the square root of the number of population in that city. Coefficients are denoted by the dots and the vertical line and whiskers denote the 95 percent confidence interval of the estimates. These solid trend lines in Panel A and C reveal a distinct downward trend starting in 2015 for urban children sample.

Figure 9: Event Study of KeyRegion on Children Outpatient Rate



(a) Urban Children



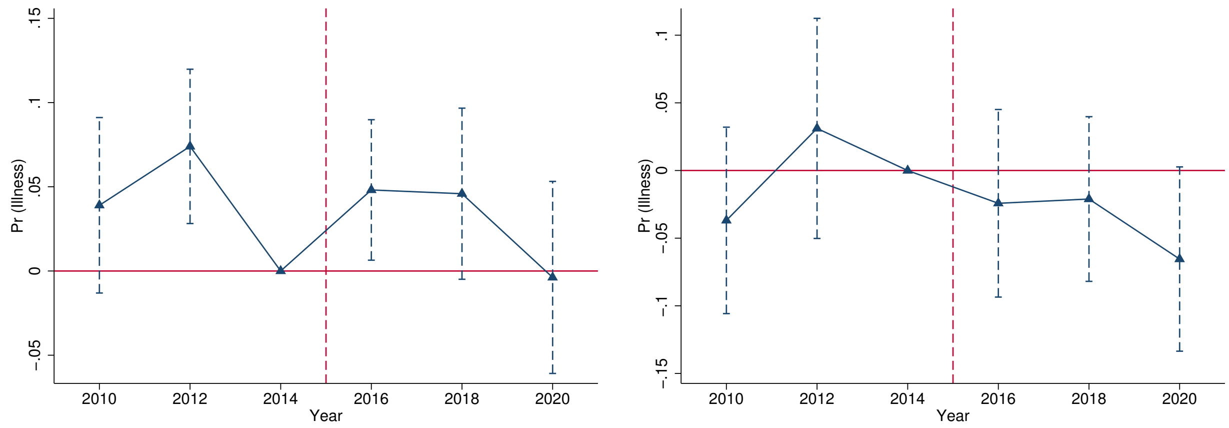
(b) Rural Children

Figure 10: Event Study of KeyRegion on Children Inpatient Rate

(a) Urban Children

(b) Rural Children

Figure 11: Event Study of KeyRegion on Children Illness Rate



(a) Urban Children

(b) Rural Children

5.2.2 Elderly Health

In addition to infant health, I also explore the impacts of the KeyRegion policy on the old people. To obtain a larger sample size covering more key region cities, I restrict the sample in CFPS who are at least 45 years of age and merge it with the CHARLS dataset.[20]

I start by looking at the reduced-form policy. Figure 12 show the event-study estimates using the chronic respiratory disease rate as the dependent variable with the same specification as in the infant and children estimation. The overall downward trends in the elderly health are consistent with the trends in infant and children in Figure 7 and Figure 8. I found KRP did not predict changes in elderly respiratory rate relative to the years before the legislation year. Panels (a) and (b) indicate that the KRP led to significant improvements in the respiratory rate for urban elderly, but not for rural elderly as expected.

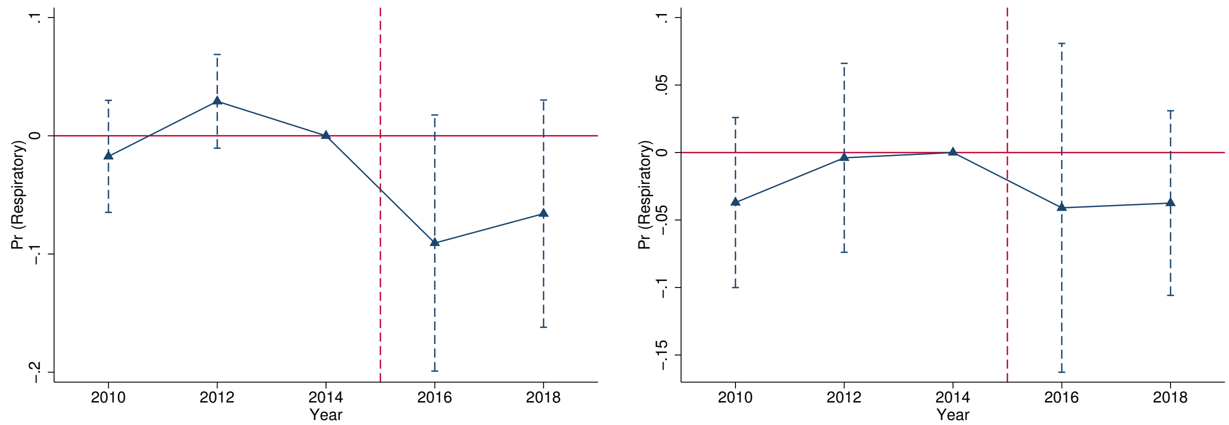
To exploit the KRP on elderly health, I first employ the CFPS dataset and regress a variety of health outcomes on the KRP. The results are reported in Table 6. In Column (1) to (2), I first check the pollution-related chronic using the respiratory disease as the dependent variable. The first two columns of Table 6 show that key region policy has a strongly negative impact on the probability of having Chronic Respiratory Diseases with 7.64 percent drop for urban elderly. There is no such association, however, for the rural sample. For the comprehensive chronic rate in column (3) and (4), both urban and rural sample reports a lower probability of chronic disease in the past 6 months. This also holds for an unhealth indicator in column (5) and (6).[21] In Column (7) and (8), I employ

[20]CFPS has a large sample size, covering individuals at all ages; while CHARLS focuses on the elderly ages over 45.

[21]The CFPS asks whether you feel uncomfortable during the last two weeks.

a binary variable based on the self-rating of health status ranging from 1 (Excellent) to 5 (Poor).[22] The result suggests that the key region policy leads to a significant higher probability of feeling good for urban elderly. As for the log of medical expenditure in Column (9) and (10), the urban elderly reports a lower medical expenditure, though the result is not statistically significant.

Figure 12: Event Study of KeyRegion on Respiratory Diseases Rate



(a) Urban Elderly

(b) Rural Elderly

Notes: The panels plot event study estimates of key region policy on elderly chronic respiratory diseases rate using CFPS dataset across rural/urban type. The regression includes year fixed effects, city fixed effects, and controls for the age, age's square, gender type, education years, marriage status and log of income. The regression is weighted by the square root of the number of population in that city. Coefficients are denoted by the dots and the vertical line and whiskers denote the 95 percent confidence interval of the estimates. These solid trend lines in Panel A reveal a distinct downward trend starting in 2015 for urban elderly sample.

Table 7 shows the results for the impacts on health outcomes among the age-eligible people while using CHARLS dataset. The first column presents the impact of the key region policy on the chronic rate and indicates that the policy significantly reduces the probability of chronic by 2.7 percent among the elderly. Chronic respiratory diseases are chronic diseases of the airways and other parts of the lung, including asthma, occupational lung diseases and so on. The next two columns present the the detailed chronic disease, and I employ the information on asthma and lung chronic disease. More specifically, the KRP significantly reduces rate of asthma and lung chronic disease by 0.06 percent and 1.3 percent, respectively. The column (4) and (5) are the measure of Limitations in Activities of Daily Living (ADL) and Limitations in Instrumental Activities of Daily Living (IADL), which can describe the people's difficulty in doing daily activities. The negative coefficients show that better air quality also increases the daily life physical be-

[22] I denote the self-rating variable equals 0 when individual reports 1 (excellent), 2 (very good), 3 (good) and 4 (fair). And it takes 1 if the answer is 5 (poor).

Table 6: Impacts on Elderly Health: CFPS Sample

	Respiratory (Yes=1)		Chronic (Yes=1)		BadHealth (Yes=1)		Self-rating (Good=0, Bad=5)		Log(Med.Exp) Log	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
KeyRegion × Post	-0.021	-0.0764[b]	0.005	-0.018	-0.003	-0.030	-0.018	-0.169[b]	0.382[b]	-0.278
	(0.027)	(0.034)	(0.023)	(0.025)	(0.013)	(0.027)	(0.092)	(0.083)	(0.169)	(0.219)
Obs.	3819	2919	19569	12353	14726	8855	14726	8855	5252	3403
R^2	0.053	0.055	0.073	0.070	0.101	0.108	0.248	0.396	0.089	0.163
Year FE	X	X	X	X	X	X	X	X	X	X
City FE	X	X	X	X	X	X	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals aged 45 and over. The covariatesin the regressions in each column include dummies for gender, age, age's square, education years, marriage status, log of income, survey year and city fixed effect. All regressions are weighted by the inverse of the square root of the number of population for each cities to control for the potential concern of uneven distribution of survey participants across different cities. All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by [a], [b], and [c], respectively.

havior.

Table 8 shows the results using both CFPS and CHARLS dataset. The first two columns report the chronic rate with negative coefficients. Columns 3 and 4 show the same specifications and present the mental health effect, and the results are also negative. Overall, the key region policy yields a better health outcome for the elderly.

Table 7: DID impacts on the Elderly: CHARLS Sample

Data	CHARLS				
Dependent Variables	Chronic (Yes=1)	Asthma (Yes=1)	Lung (Yes=1)	ADL (Yes=1)	IADL (Yes=1)
	(1)	(2)	(3)	(4)	(5)
KeyRegion × Post	-0.0278[c]	0.0002	0.0131[c]	-0.024[b]	-0.014
	(0.016)	(0.006)	(0.007)	(0.009)	(0.010)
Observations	37588	29923	29393	29373	43329
R^2	0.069	0.021	0.044	0.076	0.151
Year FE	X	X	X	X	X
City FE	X	X	X	X	X

Notes: The sample is from the CHARLS (2011-2018) for individuals aged 45 and over. The covariates in column (1) to (5) include dummies for gender, age, age's square, education years, marriage status, smoking status, survey year and city fixed effect. And in column (6) and (7) the smoking stats is dropped. All regressions are weighted by the inverse of the square root of the number of population for each cities to control for the potential concern of uneven distribution of survey participants across different cities. All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by [a], [b], and [c], respectively.

6 Heterogeneity

In this part, I analyze the heterogeneous effect of environmental regulation on locals by work type, gender, education and pollution concentration.

6.1 Who are lost? DID results across work types

In this subsection, I first exploit the fact that individuals whose jobs have different pollution intensities are affected differently. For example, the manufacturing, mining, construction, and transportation workers are believed to reveive more regulation pressure because of the characteristics of the polluting industries they take.[23] Also, many workers are directly exposed to the emission from manufacturing firms and work outside with low salary and long work hours. Overall, the working environment and job intensity make those people more exposed to the pollution concentrations.

To examine whether individuals across work types would have different health benefits effect, I estimate Equation 1 by separating the sample as worker and other according to their work type. I denote the work type is worker if the individuals take the manufac-

[23]These industries were chosen because they were viewed as major contributors to the PM2.5 concentrations and were also emphasized in the content of Key region policy. By the requirement of key region policy, these industries and jobs need to be regulated carefully with an additional focus in each cities.

Table 8: DID impacts on the Elderly: CHARLS and CFPS Sample

Data	CHARLS and CFPS			
Dependent Variables	Chronic (Yes=1)	Chronic (Yes=1)	Depression (Yes=1)	Depression (Yes=1)
	(1)	(2)	(3)	(4)
KeyRegion × Post	-0.0094	-0.0158	-0.0145[b]	-0.017[b]
	(0.009)	(0.010)	(0.006)	(0.007)
Observations	111119	111119	138351	138351
R^2	0.053	0.059	0.056	0.059
Year FE	X		X	
City FE	X	X	X	X
Province-Year FE		X		X

Notes: The sample is from the merged CHARLS (2011-2018) and CFPS (2010-2020) for individuals ages 45 and over. The covariates in column (1) to (4) include dummies for gender, age, age's square, education years, marriage status, survey year and city fixed effect. All regressions are weighted by the inverse of the square root of the number of population for each cities to control for the potential concern of uneven distribution of survey participants across different cities. All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

turing, mining, construction, and transportation jobs. In Table 9, the dependent variables are the same as the above. I control for city fixed effect and year fixed effect in all columns. The regression results show that the individual who take more polluting-intensive jobs bear more regulation costs, as measured by higher rate of chronic disease, bad health self-rating, outpatient and log of medical expenditure. The respiratory rate reduction is also not significant for those elderly whose take polluting-intensive jobs.

6.2 DID results across gender

Sample by gender.- The heterogeneous impacts on health across gender is also documented in previous studies. So I separate the sample by gender type. Table 10 show the coefficients. Overall, the KRP has more significant impacts on female elderly and young boy in terms of respiratory rate.

6.3 DID results across education

Sample by education level.- In Table 12, I separate sample by years of education as 4 quartiles of the education years distribution. The previous studies documented that less educated individuals may be more vulnerable to air pollution because they do not have

Table 9: The Effect of Regulation on Household Outcomes by Work Type: CFPS Dataset

	Respiratory		Chronic		Badhealth		Outpatient		Log Med. Exp	
	Worker	Other	Worker	Other	Worker	Other	Worker	Other	Worker	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
KeyRegion × Post	0.021	-0.131^{a}	0.036	0.021	0.018	-0.030	-0.010	0.052	-0.115	-0.096
	(0.050)	(0.042)	(0.046)	(0.043)	(0.039)	(0.022)	(0.091)	(0.054)	(0.326)	(0.255)
Obs.	2267	631	8799	3544	6166	2682	3012	968	2276	1119
R^2	0.060	0.145	0.060	0.060	0.123	0.060	0.070	0.159	0.171	0.157
Year FE	X	X	X	X	X	X	X	X	X	X
City FE	X	X	X	X	X	X	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals ages 45 and over. The covariates in all regressions include dummies for gender, age, age's square, education years, marriage status, log of household income, survey year and city fixed effect. Standard errors are clustered at the city level. All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

Table 10: The Effect of Regulation on Elderly by Gender: CFPS Dataset

	Respiratory		Chronic		Badhealth		Outpatient		Log Med. Exp	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
KeyRegion × Post	-0.036	-0.119^{b}	0.035	0.038	-0.011	-0.014	-0.087	0.105	0.039	-0.021
	(0.050)	(0.049)	(0.029)	(0.051)	(0.021)	(0.028)	(0.075)	(0.066)	(0.202)	(0.265)
Obs.	1510	1393	6757	5590	4986	3860	1882	2107	1713	1684
R^2	0.092	0.065	0.066	0.064	0.097	0.120	0.108	0.087	0.189	0.147
Year FE	X	X	X	X	X	X	X	X	X	X
City FE	X	X	X	X	X	X	X	X	X	X

Notes: Standard errors are clustered at the city level. KeyRegion equals 1 if a city is denoted as the Key region cities for controling pollution; otherwise, KeyRegion equals 0. Post equals 1 for all years after 2015 (legislation period); otherwise, Post equals 0. All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

Table 11: The DID Estimates of Regulation on Chilren by Gender

	Respiratory		Illness		Outpatient		Log of Med. Exp	
	Male	Female	Male	Female	Male	Female	Male	Female
KeyRegion × Post	-0.088^c	-0.031	-0.025	0.014	-0.039	-0.026	-0.196^b	0.030^c
	(0.050)	(0.044)	(0.020)	(0.018)	(0.026)	(0.030)	(0.086)	(0.018)
Obs.	6474	5825	9861	8854	8378	7641	6901	6099
R^2	0.096	0.136	0.090	0.088	0.128	0.134	0.155	0.083
Year FE	X	X	X	X	X	X	X	X
City FE	X	X	X	X	X	X	X	X

Notes: Standard errors are clustered at the city level. KeyRegion equals 1 if a city is denoted as the Key region cities for controling pollution; otherwise, KeyRegion equals 0. Post equals 1 for all years after 2015 (legislation period); otherwise, Post equals 0. All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

sufficient knowledge or information about air pollution, thus they would invest less into the health protection.

However, my results are not consistent with this prediction. The column (1) show that the elderly with the least education level would receive lower rate of respiratory. The coefficients are significant and larger in magnitude, indicating that those people receive more health benefits from the stringent air quality regulation. To exploit the reson, I also report the mean value of respiratory rate in different education quantiles. The people with the smaller education levels have the largest mean value of respiratory rate, which explains why the reduction of pollution affects them most.

6.4 DID results across pollution intensity

Sample by pollution level.- If better health outcomes are indeed caused by regulation-induced pollution reduction, then the impact should concentrate mainly on individuals who are more exposed to ambient pollution. Therefore, the people who live in high pollution areas should be more likely to have pollution-related diseases. To test this prediction, I estimate whether the effects of KRP on individual health benefits vary across quartiles of the pollution intensity distribution.

Table 13 and Table 14 show those results. Column (2) and (3) of Table 13 show that elderly in the most polluting-intensive area have larger probability to report the respiratory rate and chronic rate. Column (2) of Table 14 also show that children in the most polluting-intensive area have higher probability to report the reduced preterm birth rate. However, column (3) of Table 14 show that the children in high pollution area report high level of respiratory rate. This may because the pollution level in those areas is still high.

Table 12: Heterogeneity in KeyRegion's Effects By Education: CFPS Dataset

Data	CFPS Elderly				
Dependent Variables	Respiratory (Yes =1)	Chronic (Yes =1)	Badhealth (Yes=1)	Outpatient (Yes=1)	Log Med.Exp (RMB(Yuan))
	(1)	(2)	(3)	(4)	(5)
KeyRegion × Post $\times Q_1$	-0.0894^a	0.0211	0.076	0.0426	-0.060
	(0.015)	(0.048)	(0.079)	(0.135)	(0.358)
Mean	0.0947				
KeyRegion × Post $\times Q_2$	-0.105^a	0.049	-0.021	-0.015	0.128
	(0.019)	(0.060)	(0.056)	(0.086)	(0.257)
Mean	0.1089				
KeyRegion × Post $\times Q_3$	-0.0107	-0.009	-0.008	0.065	0.038
	(0.041)	(0.032)	(0.017)	(0.055)	(0.126)
Mean	0.0827				
KeyRegion × Post $\times Q_4$	-0.0261	0.028	-0.004	-0.010	-0.030
	(0.038)	(0.019)	(0.016)	(0.045)	(0.126)
Mean	0.0763				
Observations	2986	12655	9037	4084	3597
R^2	0.050	0.054	0.096	0.073	0.147
Year FE	X	X	X	X	X
City FE	X	X	X	X	X

Notes: The column (1) to (5) employ the urban elderly sample aged over 45 from CFPS dataset. The covariates in the regressions in each column include age and its square, and dummies for gender, education level, marriage status and log of income. All the standard errors are clustered at the city level in parentheses. All regressions are also weighted by the population size in each city. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

Table 13: Heterogeneity in KeyRegion's Effects By Pollution Intensity

Data	All Cities	CFPS Elderly			
Dependent Variables	$PM_{2.5}$ ($\mu g/m^3$) (1)	Respiratory (yes =1) (2)	Chronic (yes =1) (3)	Self-Rating (Good=0, Bad=1) (4)	Log Med.Exp (RMB(Yuan)) (5)
KeyRegion $\times$ Post $\times Q_1$	1.784	-0.024	0.0506	0.034	0.554^a
	(1.752)	(0.032)	(0.034)	(0.057)	(0.143)
KeyRegion $\times$ Post $\times Q_2$	-1.954^b	-0.035	0.0278	-0.067	-0.548^b
	(0.845)	(0.067)	(0.061)	(0.109)	(0.231)
KeyRegion $\times$ Post $\times Q_3$	-3.432^a	-0.051	0.0152	0.018	-0.199
	(0.914)	(0.034)	(0.026)	(0.065)	(0.200)
KeyRegion $\times$ Post $\times Q_4$	-1.337	-0.093^b	-0.139^a	-0.092	-0.222
	(1.450)	(0.038)	(0.049)	(0.107)	(0.470)
Observations	2,064	2847	12043	8631	3323
R^2	0.937	0.046	0.046	0.407	0.126
Year FE	X	X	X	X	X
City FE	X	X	X	X	X

Notes: The column (1) report the city-level $PM_{2.5}$ reduction affected by KeyRegion policy across different pollution intensity. The column (2) to (5) employ the urban individuals aged over 45 from CFPS dataset. The covariates in the regressions in each column include age and its square, and dummies for gender, education level, marriage status and log of income. All the standard errors are clustered at the city level in parentheses. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

Table 14: Heterogeneity in KeyRegion's Effects By Pollution Intensity: Children Health

Data	CFPS Infants		CFPS Children			
Dependent Variables	Low Birthweight (Yes =1)	Preterm (Yes =1)	Respiratory (Yes =1)	Illness (Yes =1)	Outpatient (Yes=1)	Log Med.Exp (RMB(Yuan))
	(1)	(2)	(3)	(4)	(5)	(6)
KeyRegion × Post $\times Q_1$	-0.009	0.010	-0.121^a	0.0352^c	-0.0306	-0.0714
	(0.033)	(0.045)	(0.032)	(0.020)	(0.046)	(0.106)
KeyRegion × Post $\times Q_2$	0.014	0.0004	-0.0109	-0.0381^c	0.0197	-0.128^c
	(0.025)	(0.024)	(0.056)	(0.021)	(0.026)	(0.045)
KeyRegion × Post $\times Q_3$	-0.007	0.004	-0.0420^c	0.0204	-0.0559^a	-0.0255
	(0.016)	(0.016)	(0.023)	(0.019)	(0.018)	(0.077)
KeyRegion × Post $\times Q_4$	-0.002	-0.0380^c	0.0674^b	-0.00644	0.00281	-0.00516
	(0.012)	(0.019)	(0.032)	(0.037)	(0.032)	(0.095)
Observations	1569	2528	11498	17372	14826	12190
R^2	0.118	0.076	0.101	0.070	0.120	0.137
Year FE	X	X	X	X	X	X
City FE	X	X	X	X	X	X

Notes: The column (1) report the city-level $PM_{2.5}$ reduction affected by KeyRegion policy across different pollution intensity. The column (2) to (5) employ the urban individuals aged over 45 from CFPS dataset. The covariates in the regressions in each column include age and its square, and dummies for gender, education level, marriage status and log of income. All the standard errors are clustered at the city level in parentheses. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

7 Mechanisms

In this section, I examine how the KeyRegion policy increase the household welfare through various mechanisms. I find that both the pollution emission side and household responsive behavior play a significant role in yielding positive health improvements.

7.1 Shutdown of polluting firms in Key Region Cities

The manufacturing firms account for the most part of pollution emission in China. A large amount of literature leverages on the shutdown of regional industrial firms to examine the effect of environmental regulation on local labor market and health outcomes (Tanaka, 2015; Hanna and Oliva, 2015).

To improve the regional pollution quality, local government set sevearl standards for those industrial firms, including shutdown, and abatement investment, and output regulation. Liu et al. (2017), Chen et al. (2018), Karplus et al. (2018) and Liu et al. (2021) show that the China environmental regulation effectively induce firm to employ multiple approaches to reduce their emissions. Therefore, this would further increase the regional household health outcomes.

The China Statistical Yearbook reports the number of "enterprise above designated size" and its annual output value. This firm definition is a commonly used statistical term to identify the industrial firm with annual main business income above 20 million RMB (280 000 USD). Therefore, one direct mechanism is to examine these large industrial firm's performance among key region cities affected by KRP.

To investigate the role of local industrial firms in affecting health, I examine whether KeyRegion policy affect number of firms and value of output. Columns (1) and (2) of Table 15 report the results separately. Here I find that the number of industrial firms drop by 8.31 percent and value of output drop by 7.1 percent after legislation. Figure 13 plots event study estimates for industrial firms. Again, there are no clear pre-trends for both measures. The number and value of industrial firms in key region cities decrease relative to control group since year of 2015.

Table 15: Mechanisms - Shutdown of firm

Dependent Variables	Log (Number of Industrial Firm)	Log (Value of Industrial Firm Output)
	(1)	(2)
KeyRegion × Post	-0.0831^c	-0.0710^c
	(0.042)	(0.036)
Observations	2064	1504
R^2	0.968	0.986
City Characteristic Control	X	X
Year FE	X	X
City FE	X	X

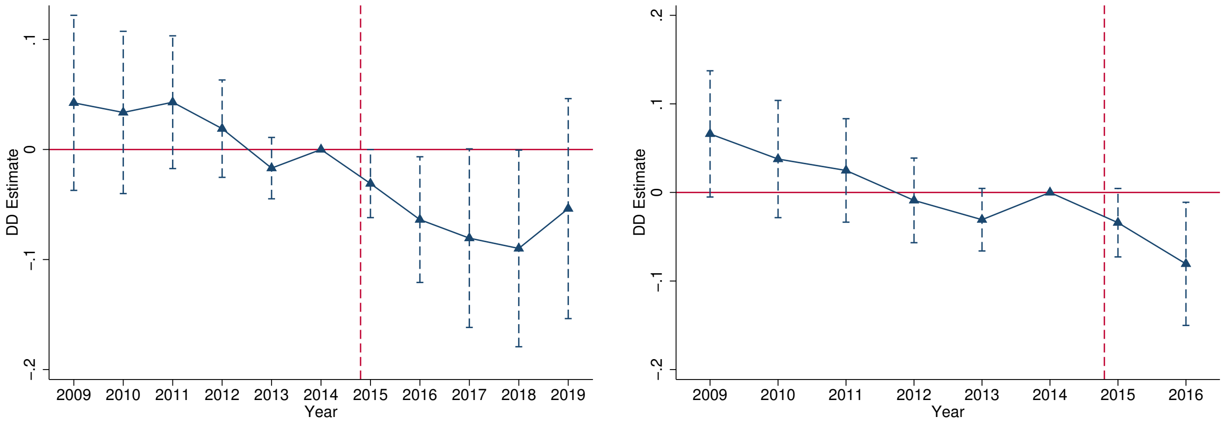
Notes: The sample is China Statistical Yearbook from 2009-2019. The two columns control for the GDP per capita, population, share of secondary industry over the gdp, share of labor in manufacturing industry and fiscal expenditure, year fixed effects and city fixed effects. All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

7.2 Information and avoidance behaviors

The responsive behavior is widely documented in previous studies. Marcus (2021) finds the information about leaks would increase the probability of household moving and have better health outcomes. Also, Zhang and Mu (2018) show that Chinese urban residents would purchase more particulate-filtering facemasks to protect against ambient air pollution. Greenstone et al. (2022) examine the automatic pollution monitoring as a key part of China's "war on pollution" since 2013 to show that this reduce manipulation and increase the people's avoidance behavior by buying more anti-haze mask and air purifiers.

Following Greenstone et al. (2022), I choose China Baidu's search indices for "anti-haze mask" and "air filters" to measure behavioral responses through online searches.

Figure 13: Event-Study Estimates for Local Industrial Firms



(a) Number of Industrial Firms

(b) Value of Industrial Firm's Output

Notes: The panels plot event study estimates of KeyRegion policy on regional industrial firm's performance. Data is from China Statistical Yearbook 2009-2019. The data of value of output of industrial firms is only available before year of 2016. The regression controls for year fixed effects, city fixed effects and annual city-specific economic controls. Brackets denote 95 percent confidence intervals, calculated from robust standard errors clustered at the city level. The reference year is 2014.

Besides, I also complement the search of pollution intensity to measure household's attention on environment issues, for example, "haze" and "environmental pollution".[24] I use the search indices from both PC and mobile terminals. The results are presented in Table 16 column (1) to (4), which show that the KeyRegion policy significantly increase regional individual's information search about haze and environmental pollution and avoidance behavior with higher seach for anti-haze mask and air purifier. These findings are consistent with existing work showing that the household has more avoidance behaviors since China's war on pollution (Greenstone et al., 2022).

The CFPS also provides the information whether the household owned an air purifier in the survey year. This question come to the survey questionnaire in the wave of 2018.[25] Column (5) in Table 16 directly checks this relationship based on the 2018 survey. The cross-section OLS estimation show that individuals from key region cities are more likely to equip the air purifier in their house, providing direct supportive evidence of the effects on purchasing behavior, though one needs to interpret the result as only a correlation.

[24]Baidu is the biggest search engine in China and provides search indices for specific keywords that are analogous to Google Trends. The first two measures employed by Greenstone et al. (2022) represent the behavior responses, and the last two measures would imply the household's focus on the air quality through information search.

[25]The household information in wave of 2020 has not been published, so only 2018 wave provide this information

7.3 Lifestyle change

In this subsection, I complement the evidence of lifestyle change such as doing exercises, physical exercises hours, sleep hours and work hours as the mechanisms for the health channel. The previous studies document the negative effect of pollution on less sleep (Heyes and Zhu, 2019), less physical hours and less working intensity.

As a response to the lower pollution caused by the environmental regulation, the individual may change their lifestyle to improve physical health and alleviate the mental stress. Therefore, it is direct to examine whether or not the high pollution concentration induce more hours of physical time and better sleeping quality.

The CFPS documents the doing exercises, physical hours, sleeping and working time. I find that urban elderly change their lifestyle as a response to environmental regulation by have more sleep hours and less weekly work hours, which is documented in column (6) and (8) in Table 17. The reduced pollution concentrations bring better sleeping quality and can help improve elderly health status. Also, the urban elderly invests less weekly work hours and physical hours to reduce the exposure to the pollution concentrations, thus help increase their health outcomes. Overall, the physical hours, sleeping time and weekly work hours among the elderly could be a mechanism explaining the health benefits of reduced pollution induced by key region policy.

Table 16: Mechanism - Information Search and Avoidance Behavior

Data	Baidu Search Index				CFPS
Dependent Variables	Haze	Env. Pollution	Anti-Haze Mask	Air purifier	Air Purifier (Yes=1)
	(1)	(2)	(3)	(4)	(5)
KeyRegion					0.036^a
					(0.003)
KeyRegion × Post	27.99^a	7.612^a	1816^a	9986^a	
	(5.338)	(1.546)	(384.9)	(1565)	
Obs.	1751	1751	1778	1778	12369
R^2	0.828	0.932	0.692	0.874	0.007
Year FE	X	X	X	X	
City FE	X	X	X	X	X

Notes: The sample in column (1) to (4) is from the China's Baidu Index from 2011 to 2020. Column (5) is cross-sectional regression using the wave of 2018 of CFPS. The covariates in column (1) to (4) include the GDP per capita, population, share of secondary industry over the gdp, share of labor in manufacturing industry and fiscal expenditure, year fixed effects and city fixed effects. The covariates in column (5) include dummies for gender, age, age's square, education years, marriage status, log of income, survey year and city fixed effect and this regression is weighted by the inverse of the square root of the number of population for each cities. All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

Table 17: Mechanism - Lifestyle Change

Data	CFPS							
Dependent Variables	Doing Exercise (Yes=1)		Physical Hours (Hours)		Sleep Hours (Hours)		Weekly Work Hours (Hours)	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KeyRegion × Post	-0.518[b]	-0.226	29.82	-7.142	-0.128	0.272[c]	-0.4198	-4.542[a]
	(0.204)	(0.210)	(52.98)	(15.69)	(0.133)	(0.146)	(1.527)	(1.635)
Obs.	11508	10107	10396	6665	18814	12154	8649	5384
R^2	0.401	0.186	0.502	0.630	0.152	0.200	0.142	0.079
Year FE	X	X	X	X	X	X	X	X
City FE	X	X	X	X	X	X	X	X

Notes: The sample is from the CFPS (2010-2020) for individuals aged 45 and over. The covariates in all column include dummies for gender, age, age's square, education years, marriage status, log of income, survey year and city fixed effect. All regressions are weighted by the inverse of the square root of the number of population for each cities to control for the potential concern of uneven distribution of survey participants across different cities. All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by [a], [b], and [c], respectively.

8 Robustness check

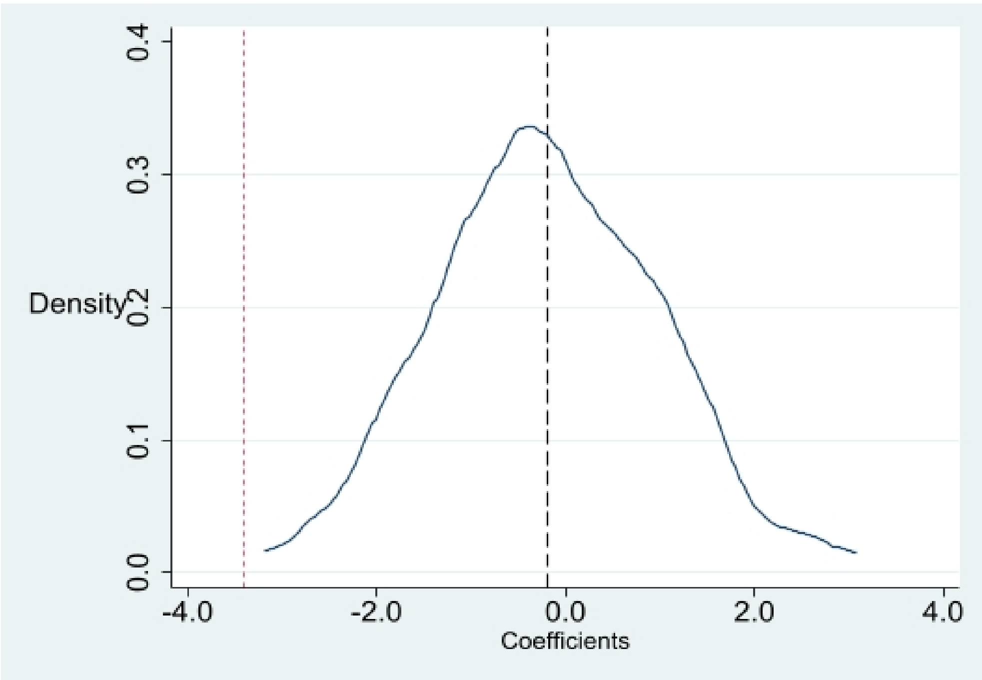
I now provide a thorough discussion of the different threats to the validity of my estimates: I first consider potential failures of the key region status, then I discuss identification and endogeneity issues in my DID specification.

8.1 Random selection

In the first robustness check, I randomly select the key regions and regress the pollution level on the treatment variables 500 times.

Figure 14 show that the 500 times coefficient is close to zero, while the actual estimates is negative 3.8. As one can see, the distribution of the coefficient is more like a normal distribution, with the mean close to 0. This gives us more convincing evidence about the plausibility of my identification strategy. Therefore, I could infer that the key region policy significantly reduce the pollution level.

Figure 14: Placebo Tests: The effect of KRP on pollution



Notes: This figure shows the results of a robustness check for Table 3, which examines the role of key region in explaining the reduction in overall pollution concentrations. In this figure, I conduct a placebo exercise, where I randomly re-assign key region status to each cities. The figure shows the results of 500 replications of this placebo exercise. The distribution of these standard deviations is plotted in blue solid line. The true value is shown in the red line.

8.2 Alternative Chronic Diseases

I also explore the heterogeneous effects of various types of chronic disease. The CFPS and CHARLS survey provides detailed information about the incidence of chronic disease and 14 different types of illness in the last 4 weeks, respectively.

In column (1)-(3) of Table 18, I estimate the impact on three chronic diseases other than respiratory using CFPS dataset. I find the KRP do not significantly decrease the chance of these three chronic disease. The columns (4)-(6) report the impacts on cancer, liver and kedney illnesses using CHARLS dataset. Again, the coefficients are statistically insignificant, indicating no significant effect on the three illnesses. Overall, the insignificant results on alternative chronic disease and illness types further confirm the effectiveness of key region policy in reducing pollution-related chronic disease.

Table 18: Robustness: Impacts on Alternative Chronic Diseases

Data	CFPS Elderly (Urban Sample)			CHARLS Elderly		
Dependent Variables	Circulatory (Yes=1)	Digestive System (Yes=1)	Infectious (Yes=1)	Cancer (Yes=1)	Liver (Yes=1)	Kidney (Yes=1)
	(1)	(2)	(3)	(4)	(5)	(6)
KeyRegion × Post	-0.002	0.008	-0.006	-0.004	-0.002	0.006
	(0.039)	(0.019)	(0.009)	(0.003)	(0.006)	(0.007)
Observations	29629	29629	29629	30157	29851	29590
R^2	0.134	0.033	0.011	0.007	0.015	0.026
Year FE	X	X	X	X	X	X
City FE	X	X	X	X	X	X

Notes: The sample in column (1) to (3) is from the CFPS (2010-2020) for individuals aged 45 and over. The sample in column (4) to (6) is from the CHARLS (2011-2018) for individuals aged 45 and over. All regressions are weighted by the inverse of the square root of the number of population for each cities to control for the potential concern of uneven distribution of survey participants across different cities. All the standard errors are clustered at the city level. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

8.3 Alternative pretreatment period

Table 19 and 20 presents the results of the main model estimation in the pretreatment period using the different treatment year and the same specification used in prior analysis. These results suggest that the pre-trends of these outcomes are not significantly relevant to the timing of the key region policy implementation. The insignificant coefficients in column (2) to (5) in Table 19 indicate that the pre-period policy do not improve elderly health outcomes. Column (1) to (4) in Table 20 indicate that the pre-period policy do not improve children and infant health outcomes.

Table 19: Placebo Tests - Main Model Estimation in Pre-Period

Data		CFPS Elderly (Urban Sample)			
Dependent Variables	$PM_{2.5}$	Respiratory	Chronic	Bad Health	Self-Rating
	(1)	(2)	(3)	(4)	(5)
Panel A: Suppose policy in 2013					
KeyRegion × Post	-1.801[b]	-0.0192	-0.0103	-0.0128	-0.0189
	(0.680)	(0.016)	(0.021)	(0.018)	(0.066)
Panel B: Suppose policy in 2012					
KeyRegion × Post	-1.267[b]	0.0209	-0.021	-0.009	0.008
	(0.549)	(0.023)	(0.033)	(0.012)	(0.062)
Panel C: Suppose policy in 2011					
KeyRegion × Post	-0.748	0.0209	-0.0213	-0.009	0.008
	(0.536)	(0.023)	(0.033)	(0.012)	(0.062)
Observations	2315	2919	12353	8855	8855
R^2	0.975	0.054	0.058	0.101	0.389

Notes: The sample in column (1) is from the AOD pollution dataset. The sample in column (2) to (5) is from the CFPS (2010-2020) for individuals aged 45 and over. The covariates in the regressions in each column include age and its square, and dummies for gender, education level, marriage status and log of income. All the standard errors are clustered at the city level in parentheses. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

Table 20: Placebo Tests - Main Model Estimation in Pre-Period

Data	CFPS Children (Urban Sample)		CFPS Infant (Urban Sample)	
Dependent Variables	Respiratory	Outpatient	Low Birth Weight	Prematurity
	(1)	(2)	(3)	(4)
Panel A: Suppose policy in 2013				
KeyRegion × Post	-0.040	-0.051[b]	-0.005	-0.0229
	(0.040)	(0.022)	(0.052)	(0.032)
Panel B: Suppose policy in 2012				
KeyRegion × Post	-0.020	0.0203	-0.138	-0.0337
	(0.041)	(0.022)	(0.133)	(0.0238)
Observations	12301	16020	1473	2455
R^2	0.104	0.118	0.125	0.066

Notes: The sample in column (1) to (4) is from the CFPS (2010-2020) for yound children under 16. The covariates in the regressions in column (1) and (2) include age and its square, and dummies for gender and education level. Column (3) and (4) controls for gender. All the standard errors are clustered at the city level in parentheses. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

8.4 Selective Migration

One common concern of estimation of health benefits of environmental regulation is selective migration (Currie et al., 2011; Currie and Walker, 2011). The assumptions necessary to identify health effects would be violated if the KeyRegion policy causes mothers with systematically different unobserved health endowments to move closer to the key region city. In order to guard against the possible effects of selective migration, I estimate the impacts of KRP on migration decision.

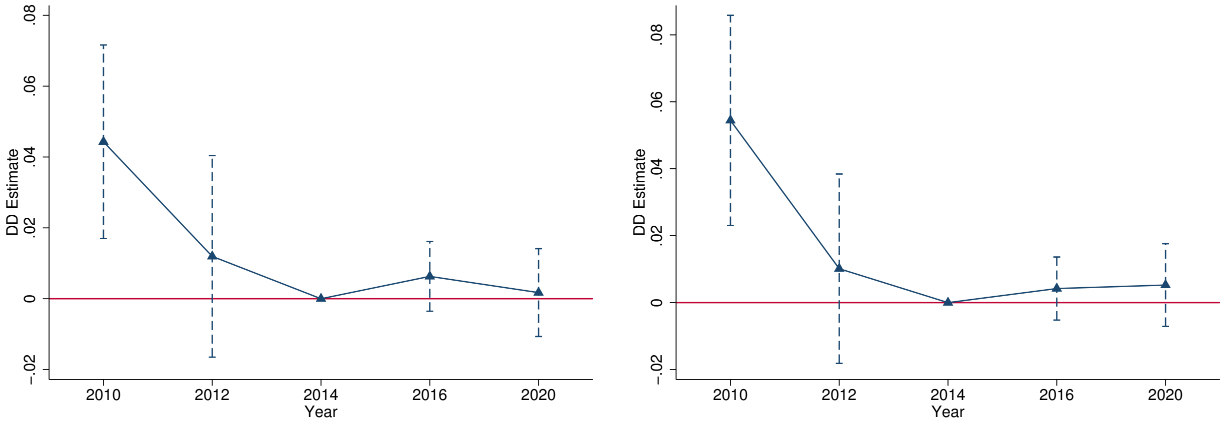
Following Huang and Zhang (2021), I choose the variable of whether migrating to another city as the measure of selective migration from the CFPS dataset. The results are shown in Table 21 and Figure 15. Figure 15 plots the trends of migration, and the results are all close to zero. Also, the coefficients in Table 21 are negative, indicating that the KRP do not induce individuals to move to another city.

Table 21: Robustness: Effects of the KeyRegion on Migration Decision

Dependent Variables	Cross-city migration (Yes=1) (1)	Cross-city migration (Yes=1) (2)
Panel A: All ages		
KeyRegion × Post	-0.0256^b	-0.0243^b
	(0.0103)	(0.00986)
Observations	88710	88710
R^2	0.026	0.038
Panel B: Ages over 45		
KeyRegion × Post	-0.0150^c	-0.0243^a
	(0.0087)	(0.00858)
Observations	50696	50696
R^2	0.027	0.041
Year FE	X	
City FE	X	X
Province-Year FE		X

Notes: The definition of cross-city migration is given in the text. The data is from the CFPS. The covariates in the regressions in each column include age and its square, and dummies for gender, education level, marriage status, year fixed effect and city fixed effect. All regressions are weighted by the inverse of the square root of the number of population for each cities. All the standard errors are clustered at the city level in parentheses. Significance at the 1%, 5%, and 10%, levels are denoted by ^{a}, ^{b}, and ^{c}, respectively.

Figure 15: Event Study Plots of Key Region policy on Migration



(a) Weighted by City Population

(b) No weighting

Notes: This figure plots event study estimates of KeyRegion policy on people's migration decision using CFPS dataset. Panel A and B report the regression with and without weighting method. The regression includes year fixed effects, city fixed effects, and controls for the age, age's square, gender type, education years, marriage status and log of income. Coefficients are denoted by the dots and the vertical line and whiskers denote the 95 percent confidence interval of the estimates. Both solid trend lines reveal an insignificant upward trend starting in 2015 for eldery, indicating that the migration decision is not affected by KRP.

8.5 Alternative confounding factors

To rule out the potential concern that my findings may be driven by family-level or city-level unobservable factors that influence all individuals, here I perform a number of tests by estimating the KRP on a set of economic indicators.

Family Characteristics.- The family-level concern may come from the fact that the legislation of the KRP can be correlated with changes in family characteristics in the estimation of infant and children. For example, if the legislation of the KRP was correlated with an increase in conceptions for family with high proclivity for prenatal care in key regions, then my results would reflect the change in the composition of families rather than the change from the air quality improvement induced by KRP. Also, it may affect the people's health behavior (e.g., smoking) when examining health outcomes of the elderly. Therefore, I first show the evidence that urban family characteristics measured by household income are not changing simultaneously with the policy exposure in column (2) of Table 22.

Another family-level confounding factor would be the parental investment. If the KPR significantly increase the parental investment on their children, then the health benefits affected by the reduced pollution would be biased. Parental investment would provide children or infants with better health care, medical access and thus better health status. Following Deng and Lindeboom (2022), here I use principal component analysis on the three children investment questions and obtain a z-score for parental investment for the children sample. [26] The estimation result in column (3) suggests that the key region policy does not induce parents to make more reinforcing investments in their children.

Finally, I also report the impacts on smoking status for elderly using both CFPS and CHARLS dataset in column (4). All of these show there is no evidence of a systematic change in underlying family and individual characteristics that corresponds to the policy variation.

Local economic change.- Another confounding concern comes from the fact that any changes in the regional economic characteristics (e.g., healthcare infrastructure, number of physicians, local wages) would affect the people's health status. If the KeyRegion policy or other confounding policies induce the key region area to increase local healthcare investments or increase local wages, then the DID estimates of health effects of KeyRegion policy would be biased. More healthcare resources would provide local people better healthcare, and higher wages would increase local people's willingness to pay for a better air quality and defensive investments, thus increase their health status. Therefore, I regress a set of city's characteristics on the KeyRegion policy to examine whether the those economic indicators make my estimates biased. The regression results are shown in column (1) to (4) in Table 23. The Figure 16 plots their event study estimates. The regression results are insignificant in general, meaning that the KeyRegion policy do not improve regional health infrastructure more compared to the non key region cities.

9 Benefits Analysis

My results provide the first ex-post evaluation of China's war on pollution. The core of the recent stringent environmental regulation is the legislation of key region policy. The key region policy led to meaningful improvements in fine particulate matter, infant health, children health and elderly health as a result of $PM_{2.5}$ regulation. Here, I conduct a simple benefit analysis for the China's war on pollution, with the caveat that data restrictions prevent us from measuring all health outcomes and costs.

First, I use the pollution measurements with my estimated effect — that 3.8 units of predicted fine particulate matter reduction from the key region policy led to a 1 percent decline in preterm birth infants. From the China Statistical Yearbook, the number of new born population among key region cities in 2017, 2018 and 2019 is 5368838, 4542177 and 4113095, respectively. So I use the year of 2017 for the baseline calculation and find that the China's war on pollution led to approximately 53688 fewer preterm birth infants in year of 2017. The average medical expenditure for caring a preterm baby is about 11780 USD in China, which translates into $0.632 billion in year of 2017.

[26] The CFPS dataset asks the questions: how often the parent read to their child; how often the parent buys books for their child; and how often they travel with their child.

Table 22: Robustness Check on Parental Characteristics

Data	CFPS			CFPS&CHARLS
Dependent Variables	Log of Income (RMB:Yuan)		Parental Inv. (Yes=1)	Smoking (Yes=1)
	(1)	(2)	(3)	(4)
	Rural	Urban		
KeyRegion × Post	-0.342[a]	0.087	-0.141[a]	0.0054
	(0.088)	(0.066)	(0.051)	(0.007)
Observations	20299	12620	9637	62568
R^2	0.540	0.429	0.168	0.411
Individual Control	X	X	X	
Year FE	X	X	X	X
City FE	X	X	X	X

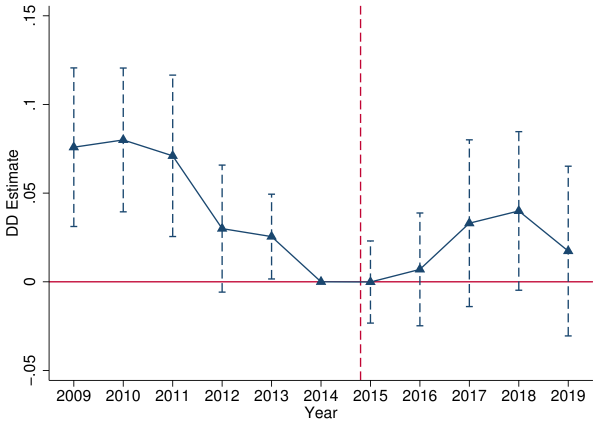
Notes: In column (1) and (2), the income data is from the CFPS with individuals aged over 45. The parental investment data in column (3) is from CFPS children questionnaire. The smoking behavior data is from both CFPS and CHARLS with individuals aged over 45. The covariates in all regressions are the same as the baseline regression. All regressions are weighted by the inverse of the square root of the number of population for each cities. All the standard errors are clustered at the city level in parentheses. Significance at the 1%, 5%, and 10%, levels are denoted by [a], [b], and [c], respectively.

Table 23: Robustness Check on City Characteristics

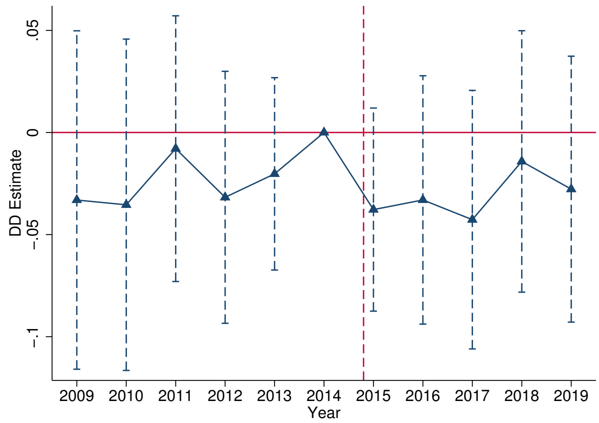
Data	China Statistical Yearbook			
Dependent Variables	Hospital beds (Log)	Physician (Log)	Government Exp (Log)	Wage (Log)
	(1)	(2)	(3)	(4)
KeyRegion × Post	-0.027	-0.010	-0.036	-0.018
	(0.017)	(0.027)	(0.025)	(0.012)
Observations	2064	2064	2064	2063
R^2	0.979	0.951	0.979	0.954
City Characteristic Control	X	X	X	X
Year FE	X	X	X	X
City FE	X	X	X	X

Notes: In column (1) and (4), the data is from the China Statistical Yearbook 2009 - 2019. These city-level regressions in each column include GDP per capita, population, share of labor in manufacturing industry and fiscal revenue. All the standard errors are clustered at the city level in parentheses. All columns absorb city fixed effect and year fixed effect. Significance at the 1%, 5%, and 10%, levels are denoted by [a], [b], and [c], respectively.

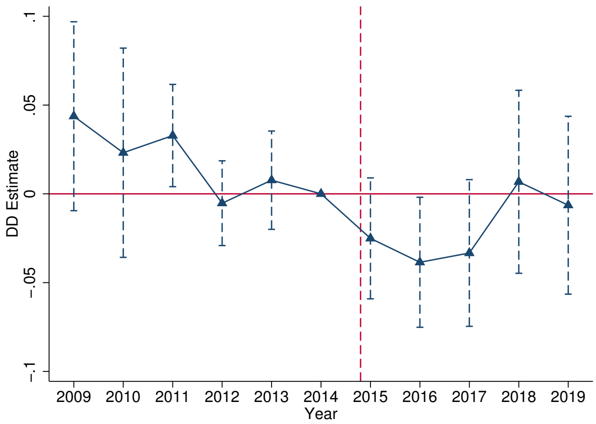
Figure 16: Robustness Check on City Characteristics



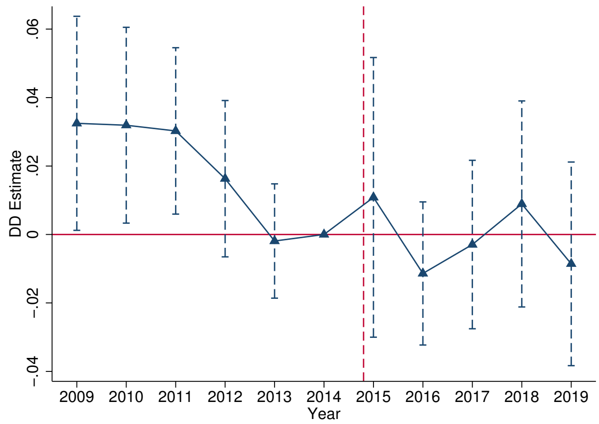
(a) Log (number of beds in hospitals)



(b) Log (number of physician)



(c) Log (government expenditure)



(d) Log (wage)

Notes: This figure plots the estimated coefficients of KeyRegion × Year dummy variables. The reference year is 2014. The regression controls for year fixed effects, city fixed effects and annual city-specific economic controls. Brackets denote 95 percent confidence intervals, calculated from robust standard errors clustered at the city level.

Column (9) of Table 5 suggests the average reduction in medical expenditure for children is 15 percent point. Specifically, the average medical expenditure from the CFPS dataset for urban children in 2016 and 2018 is 223.6 USD, which yields \$33.54 savings for a children per year.

My estimates shed light on the consequences of the stringent key region policy for health benefits. The health benefits indicates that the social welfare of better air quality is substantial. While I do not estimate the social cost of this regulation and the health benefits in this paper are informative of the infant birth outcome, more evidence and calculation can complement to this China's war on pollution.

For a comparison, a recent paper by Heo et al. (2023) quantifies the China's war on pollution and finds that annual average of transboundary $PM_{2.5}$ from China to South Korea declined by 9.63 $\mu g/m^3$, with economic benefits of \$2.62 billion per year, based on the avoided mortality. Their pollution reduction magnitude is larger than my estimates, and this is because the South Korea is close to the cities with higher pollution concentrations in China, while my estimates consider the whole average reduction in China. Besides, the avoided mortality should provide a upper bound of welfare benefits, while the savings in preterm caring in my study reflect the avoided medical expenditure. Overall, these estimates both provide a big picture about the significant welfare improvements induced by the China's war on pollution.

10 Conclusion

As one of the most essential contents during China's war on pollution, the legislation of Key Region Policy provides a important context to quantify the effectiveness and health benefits of environmental regulation. The key region cities denoted by this policy represent the main source of pollution throughout China. Using the latest wavies of CFPS and CHARLS dataset, I conduct a comprehensive analysis of the causal effect of environmental regulation on infant birth outcome, and health status of children and elderly. This paper first show that *KeyRegion* policy significantly reduce the pollution level in key cities relative to the non-key cities by 4.75 $\mu g/m^3$, about (7.9 percent), thus the control target specified by the policy was achieved.

Second, the DID results show that the key region policy reduces the probability of preterm birth by about 1 percent among urban infants living in key region cities. This policy also induce health benefits for urban children. The respiratory disease rate decrease by 6 percentage point, and the outpatient rate decrease by 4.8 percentage point. The defensive investment evidence show that the medical expenditure drop by 15 percentage point. Meanwhile, I also document the evidence of health improvements among the old people. The respiratory disease rate decreases by 7.6 percentage point, the comprehensive chronic rate decreases by 1.8 percentage point and the depression rate drops by 2.4 percentage point.

Next, I explore the heterogeneous effect of key region policy. The results further show that the people's health outcomes do not become better for those whose jobs are of high pollution intensity. Those worker's health outcomes are worse, measured by insignificant respiratory reduction, higher level of self-rating as bad health, outpatient rate and medical expenditure. This show that the workers still face relative high pollution level with the demanding work contents, and they bear more costs of the blue sky. In addition, this key region policy brings more health benefits to the elderly with low education level and elderly living in high polluting-intensive areas.

Finally, this paper examines multiple mechanisms. I find the shutdown of polluting firms play the important role of reducing the pollution concentrations. The information search and avoidance behavior is also positively related to the key region policy. I find that information mitigates the negative health effects of exposure, which is consistent with more avoidance behaviors, such as buying anti-haze masks and air purifiers.

My study contributes to the growing literature on China's environmental regulation by employing the legislation of key region policy as the key part of the China's war on pollucion in 2015 and exploiting its effectiveness and health benefits. Second, my work is also related to the literature on environmental justice and health inequality among household with different socioeconomic conditions. As a complement, my paper shows that the environmental regulation increases health disparity between workers and other work types in China.

References

Alexander, Diane and Hannes Schwandt, "The impact of car pollution on infant and child health: Evidence from emissions cheating," *The Review of Economic Studies*, 2022, *89* (6), 2872–2910.

Andresen, Elena M, Judith A Malmgren, William B Carter, and Donald L Patrick, "Screening for depression in well older adults: Evaluation of a short form of the CES-D," *American journal of preventive medicine*, 1994, *10* (2), 77–84.

Ao, Chon-Kit, Yilin Dong, and Pei-Fen Kuo, "Industrialization, indoor and ambient air quality, and elderly mental health," *China Economic Review*, 2021, *69*, 101676.

Auffhammer, Maximilian, Antonio M Bento, and Scott E Lowe, "Measuring the effects of the Clean Air Act Amendments on ambient PM10 concentrations: The critical importance of a spatially disaggregated analysis," *Journal of Environmental Economics and Management*, 2009, *58* (1), 15–26.

Bishop, Kelly C, Jonathan D Ketcham, and Nicolai V Kuminoff, "Hazed and confused: the effect of air pollution on dementia," Technical Report, National Bureau of Economic Research 2018.

Chen, Yi and Hanming Fang, "The long-term consequences of China's "later, longer, fewer" campaign in old age," *Journal of Development Economics*, 2021, *151*, 102664.

Chen, Zhao, Matthew E Kahn, Yu Liu, and Zhi Wang, "The consequences of spatially differentiated water pollution regulation in China," *Journal of Environmental Economics and Management*, 2018, *88*, 468–485.

Cherniwchan, Jevan and Nouri Najjar, "Do environmental regulations affect the decision to export?," *American Economic Journal: Economic Policy*, 2022, *14* (2), 125–60.

Currie, Janet and Reed Walker, "Traffic congestion and infant health: Evidence from E-ZPass," *American Economic Journal: Applied Economics*, 2011, *3* (1), 65–90.

_ and _ , "What do economists have to say about the Clean Air Act 50 years after the establishment of the Environmental Protection Agency?," *Journal of Economic Perspectives*, 2019, *33* (4), 3–26.

_ , Michael Greenstone, and Enrico Moretti, "Superfund cleanups and infant health," *American Economic Review*, 2011, *101* (3), 435–41.

Curtis, E Mark, "Who loses under cap-and-trade programs? The labor market effects of the NOx budget trading program," *Review of Economics and Statistics*, 2018, *100* (1), 151–166.

Deng, Zichen and Maarten Lindeboom, "A bit of salt, a trace of life: Gender norms and the impact of a salt iodization program on human capital formation of school aged children," *Journal of Health Economics*, 2022, *83*, 102614.

Deschenes, Olivier, Huixia Wang, Si Wang, and Peng Zhang, "The effect of air pollution on body weight and obesity: evidence from China," *Journal of Development Economics*, 2020, *145*, 102461.

—, Michael Greenstone, and Joseph S Shapiro, "Defensive investments and the demand for air quality: Evidence from the NOx budget program," *American Economic Review*, 2017, *107* (10), 2958–89.

Do, Quy-Toan, Shareen Joshi, and Samuel Stolper, "Can environmental policy reduce infant mortality? Evidence from the Ganga Pollution Cases," *Journal of Development Economics*, 2018, *133*, 306–325.

Dong, Yan, Jinhuan Tian, and Qiang Wen, "Environmental regulation and outward foreign direct investment: Evidence from China," *China Economic Review*, 2022, *76*, 101877.

Fan, Haichao, Joshua S Graff Zivin, Zonglai Kou, Xueyue Liu, and Huanhuan Wang, "Going green in China: Firms' responses to stricter environmental regulations," Technical Report, National Bureau of Economic Research 2019.

Fu, Shihe, V Brian Viard, and Peng Zhang, "Air pollution and manufacturing firm productivity: Nationwide estimates for China," *The Economic Journal*, 2021, *131* (640), 3241–3273.

Gong, Jie, Yi Lu, and Huihua Xie, "The average and distributional effects of teenage adversity on long-term health," *Journal of Health Economics*, 2020, *71*, 102288.

Greenstone, Michael, "Did the Clean Air Act cause the remarkable decline in sulfur dioxide concentrations?," *Journal of Environmental Economics and Management*, 2004, *47* (3), 585–611.

— and B Kelsey Jack, "Envirodevonomics: A research agenda for an emerging field," *Journal of Economic Literature*, 2015, *53* (1), 5–42.

— and Rema Hanna, "Environmental regulations, air and water pollution, and infant mortality in India," *American Economic Review*, 2014, *104* (10), 3038–72.

—, Guojun He, Ruixue Jia, and Tong Liu, "Can Technology Solve the Principal-Agent Problem? Evidence from China's War on Air Pollution," *American Economic Review: Insights*, 2022, *4* (1), 54–70.

__ , __ , **Shanjun Li, and Eric Yongchen Zou**, "China's war on pollution: Evidence from the first 5 years," *Review of Environmental Economics and Policy*, 2021, *15* (2), 281–299.

Hanna, Rema and Paulina Oliva, "The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City," *Journal of Public Economics*, 2015, *122*, 68–79.

Hansen-Lewis, Jamie and Michelle M Marcus, "Uncharted Waters: Effects of Maritime Emission Regulation," Technical Report, National Bureau of Economic Research 2022.

Hausman, Catherine and Samuel Stolper, "Inequality, information failures, and air pollution," *Journal of Environmental Economics and Management*, 2021, *110*, 102552.

Heo, Seonmin Will, Koichiro Ito, and Rao Kotamarthi, "International Spillover Effects of Air Pollution: Evidence from Mortality and Health Data," Technical Report, National Bureau of Economic Research 2023.

Heyes, Anthony and Mingying Zhu, "Air pollution as a cause of sleeplessness: Social media evidence from a panel of Chinese cities," *Journal of Environmental Economics and Management*, 2019, *98*, 102247.

Hollingsworth, Alex and Ivan Rudik, "The effect of leaded gasoline on elderly mortality: Evidence from regulatory exemptions," *American Economic Journal: Economic Policy*, 2021, *13* (3), 345–73.

Huang, Wei and Chuanchuan Zhang, "The power of social pensions: Evidence from China's new rural pension scheme," *American Economic Journal: Applied Economics*, 2021, *13* (2), 179–205.

Isen, Adam, Maya Rossin-Slater, and W Reed Walker, "Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970," *Journal of Political Economy*, 2017, *125* (3), 848–902.

Ito, Koichiro and Shuang Zhang, "Willingness to pay for clean air: Evidence from air purifier markets in China," *Journal of Political Economy*, 2020, *128* (5), 1627–1672.

Karplus, Valerie J, Junjie Zhang, and Jinhua Zhao, "Navigating and evaluating the labyrinth of environmental regulation in China," *Review of Environmental Economics and Policy*, 2021, *15* (2), 300–322.

__ , **Shuang Zhang, and Douglas Almond**, "Quantifying coal power plant responses to tighter SO2 emissions standards in China," *Proceedings of the National Academy of Sciences*, 2018, *115* (27), 7004–7009.

Khanna, Gaurav, Wenquan Liang, Ahmed Mushfiq Mobarak, and Ran Song, "The Productivity Consequences of Pollution-Induced Migration in China," Working Paper 28401, National Bureau of Economic Research January 2021.

Lai, Wangyang, "Pesticide use and health outcomes: evidence from agricultural water pollution in China," *Journal of Environmental Economics and Management*, 2017, *86*, 93–120.

Liu, Mengdi, Ronald Shadbegian, and Bing Zhang, "Does environmental regulation affect labor demand in China? Evidence from the textile printing and dyeing industry," *Journal of Environmental Economics and Management*, 2017, *86*, 277–294.

_ , Ruipeng Tan, and Bing Zhang, "The costs of "blue sky": environmental regulation, technology upgrading, and labor demand in China," *Journal of Development Economics*, 2021, *150*, 102610.

Lu, Weixue, Hecheng Wu, and Shuaishuai Geng, "Heterogeneity and threshold effects of environmental regulation on health expenditure: Considering the mediating role of environmental pollution," *Journal of Environmental Management*, 2021, *297*, 113276.

Marcus, Michelle, "Going Beneath the Surface: Petroleum Pollution, Regulation, and Health," *American Economic Journal: Applied Economics*, 2021, *13* (1), 1–37.

Tanaka, Shinsuke, "Environmental regulations on air pollution in China and their impact on infant mortality," *Journal of Health Economics*, 2015, *42*, 90–103.

van Donkelaar, Aaron, Melanie S Hammer, Liam Bindle, Michael Brauer, Jeffery R Brook, Michael J Garay, N Christina Hsu, Olga V Kalashnikova, Ralph A Kahn, Colin Lee et al., "Monthly global estimates of fine particulate matter and their uncertainty," *Environmental Science & Technology*, 2021, *55* (22), 15287–15300.

Yao, Yao, Xue Li, Russell Smyth, and Lin Zhang, "Air pollution and political trust in local government: Evidence from China," *Journal of Environmental Economics and Management*, 2022, *115*, 102724.

Zhang, Junjie and Quan Mu, "Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks," *Journal of Environmental Economics and Management*, 2018, *92*, 517–536.

Zhang, Xin, Xiaobo Zhang, and Xi Chen, "Happiness in the air: How does a dirty sky affect mental health and subjective well-being?," *Journal of Environmental Economics and Management*, 2017, *85*, 81–94.

Appendix A Data

CFPS

China Family Panel Studies (CFPS) CFPS is a biennial survey and is designed to be similar to the U.S. Panel Study of Income Dynamics. The first national wave was conducted in collaboration with the Institute of Social Science Survey at the Peking University and the Survey Research Center at the University of Michigan from April to August 2010. The five main parts of the questionnaire include data on communities, households, household members, adults, and children.

CHARLS

China Health and Retirement Longitudinal Studies (CHARLS) The CHARLS aims to collect a nationally representative sample of Chinese residents ages 45 and older to serve the needs of scientific research on the elderly. The baseline national wave of the CHARLS was fielded in 2011. The individuals are followed up every two years. This study used the 2011, 2013, 2015 and 2018 waves.

Table 24: Variable and Questionnaire in CFPS and CHARLS

Variable	Questionnaire in survey
Panel A. CFPS	
Chronic	During the past six months, have you had any doctor-diagnosed chronic disease? (1-yes; 0-no)
Respiratory	If the chronic question is yes, then what is the doctor-diagnosed chronic diseas
Self-Rating Health	What do you evaluate your current health status?
Bad Health	Self-rating health takes the value "Unhealth".
Outpatient	Have you visited doctors last 6 months? (1-yes; 0-no).
Inpatient	Were you hospitalized last year due to illness/injury? (1-yes; 0-no).
Log of Medical Expenditure	What is your total medical expenditure last year?
Panel B. CHARLS	
Chronic	Diagnosed with Chronic Lung Diseases by a Doctor (1-yes; 0-no).
Asthma	Diagnosed with Asthma by a Doctor (1-yes; 0-no)
Lung Chronic	Diagnosed with Lung Chronic by a Doctor (1-yes; 0-no)
Self-Rating Health	Self-Reported Health Status (1-5)
Log of Medical Expenditure	Total Medical Cost of Hospitalization and Inpatient
Panel C. CFPS Children	
Birth weight	What is the infant's birth weight?
Gestation period	What is the infant's gestation period?

Notes: These codes are compiled from CFPS disease codebook.

Table 25: Chronic diseases related to air pollution

Disease Code	Respiratory Diseases
12.70	Acute nasopharyngitis
12.71	Acute upper respiratory infections of the pharyngitis, tonsillitis and tracheitis
12.72	Influenza
12.73	Pneumonia
12.74	Chronic rhinitis, nasopharyngitis and pharyngitis
12.75	Emphysema
12.76	Other chronic obstructive pulmonary disease (copd, including chronic bronchitis, etc.)
12.77	Asthma
12.78	Other diseases of the respiratory system including acute lower espiratory infections and chronic sinusitis

Notes: These codes are compiled from CFPS disease codebook.

Mental Health:

The prior literature has documented a negative effect of pollution on nervous system and mental health (Heyes and Zhu, 2019; Ao et al., 2021). Here, I use *6-item Center for Epidemiologic Studies Depression (CES-D) scale* from both CFPS and CHARLS data set to depict the depression and mental health (Andresen et al., 1994). The CES-D score ranges from 0 to 18, with a higher value representing more severe depressive symptoms. The *CES-D* consists of 6 questions: (1) "Felt Depressed," (2) "I Felt Everything I Did Was An Effort," (3) "I Felt Hopeful about the Future," (4) "My Sleep Was Restless," (5) "I Was Happy," and (6) "I Could Not Get on." Interviewees respond to each of the question based on how they have felt and behaved during the last week. There are four responses for each question: rarely or none of the time (1 day), some or a little of the time (1–2 days), occasionally or a moderate amount of the time (3–4 days), or most or all of the time (5–7 days). We recoded the responses of each question from a value of 0 (rarely or none of the time) to 3 (most or all of the time), respectively. For question (3) and (5), I denote the answer of rarely or none of the time (1 day) with value 3. Therefore, the CES-D score in this paper ranges from 0 to 18, with a higher value representing more severe depressive symptom. I also created a binary variable of depressive symptoms using a cutoff of 10 (based on (Andresen et al., 1994)). This elderly health and cognition is taken from the CHARLS and is widely used in literature (e.g., Chen and Fang, 2021; Ao et al., 2021). The CES-D score for whole people is from CFPS (see, e.g., Zhang et al., 2017; Gong et al., 2020). The CFPS 2010 and 2014 use a 6-item scale, which is highly correlated with the standard 20-item CES-D scale and has adequate psychometric properties for sensitive and specific detection of depressive disorders. So I use the ces-d score and normalize it to 0-1.